Institutional Investors: Arbitrageurs or Rational Trend Chasers ☆

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Abstract

This paper studies the relationship between institutional investor holdings and stock misvaluation in the U.S. between 1980 and 2010. I find that institutional investors overweigh overvalued and underweigh undervalued stocks in their portfolio, taking the market portfolio as a benchmark. Cross-sectionally, institutional investors hold more overvalued stocks than undervalued stocks. The time-series studies also show that institutional ownership of overvalued portfolios increases as the portfolios' degree of overvaluation. As an investment strategy, institutional investors' ride of stock misvaluation is neither driven by the fund flows from individual investors into institutions, nor industry-specific. Consistent with the agency problem explanation, investment companies and independent investment advisors have a higher tendency to ride stock misvaluation than other institutions. There is weak evidence that institutional investors make a profit by riding stock misvaluation. My findings challenge the models that view individual investors as noise traders and disregard the role of institutional investors in stock market misvaluation.

Keywords: Institutional Investors, Stock Misvaluation, Factor Models

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1. Introduction

Stock market investors are classified as two broad types: arbitrageurs and noise traders.[1] Noise traders trade for non-information-based reasons and are subject to systematic biases on their stock return expectations. In contrast, arbitrageurs form rational expectations based on the available information and correct any stock misvaluation caused by the trading of noise traders. The existence of noise traders subsidizes arbitrageurs' information production cost (Grossman and Stiglitz, 1980). In reality, the participants in the stock market are composed of institutional investors and individual retail investors. The previous literature regarded sophisticated institutional investors as informed arbitrageurs and behavioral individual investors as noise traders, which leads to a question. Why does stock misvaluation still persist in a stock market which institutional investors dominate in terms of both market share and trading volume? To better understand the role of institutions in stock market misvaluation, I investigate the institutional holdings of mispriced stocks in the U.S. stock market.

Although the efficient market hypothesis precludes the existence of long-term stock misvaluation, the presence of mispriced stocks has been widely documented. For individual stocks, some famous examples are the mispricing of carve-outs when 3COM spun off its Palm unit in March 2000; the dual-listed stock price discrepancies for Infosys on March 7, 2000; and the price gaps between Royal Dutch and Shell from 1907 to 2005. Other examples of misvaluation on the stock market level are the Japanese stock market bubble in the late 1980s', the Dot-com bubble in the late 1990s', and the real estate bubble in 2007. Indeed, there has been a long debate on the existence of stock bubbles in the previous literature.[2] But a common consensus that stock prices may deviate from their intrinsic

[1]Other common names for arbitrageurs are rational speculators and smart money. Noise traders are also known as behavioral traders, liquidity traders, irrational investors, or dumb money.

[2]For example, Cochrane (2002) argues that internet stocks were in short of supply during the "Dot-com bubble" boom because the lock-up period after the initial public offerings of technology companies limited the shares of internet firm stocks traded in the stock market. The limited outstanding shares of internet stocks provided a convenience yield for investors to hold the floating shares, which explains the overvaluation of internet stocks.

value, at least in the short-run, has been reached.

Why do rational arbitrageurs fail to drive stock prices back to their intrinsic value? Among all the explanations for the failure of arbitrage, three are generally accepted by most researchers. Firstly, both fundamental risk and noise trader risk cause an unpredictability of future returns on mispriced stocks (Black, 1985; Mitchell et al., 2002; Lamont and Thaler, 2003). Secondly, stock misvaluation can only be corrected if arbitrageurs collectively trade against it. But the synchronization among arbitrageurs is hard to achieve in practice (Abreu and Brunnermeier, 2002, 2003). Thirdly, heterogenous investor opinions and short sale constraints limit the arbitrage, so that only good information is reflected in stock prices (Miller, 1977; Diether et al., 2002; Jones and Lamont, 2002). However these theories may not fully explain the persistence of stock misvaluation in the U.S. stock market.

In 1950, 90% of U.S. corporate equities were held by individual investors (Allen, 2001). At that time, even if institutions[3] traded against stock misvaluation, they might not have sufficient capital to correct stock mispricing promptly. Gradually, the U.S. stock market has become more institutionalized. According to Gompers and Metrick (2001), the largest one hundred institutions controlled more than half of the market value of U.S. publicly traded equities in 1996. Ferreira and Matos (2008) also report that the institutional stock holdings accounted for 65.7% of the U.S. stock market value in 2005, 59.6% if held domestically. The previous empirical literature shows that institutions are better informed and less likely to be affected by irrationality than individual investors (Griffin et al., 2003; Barber et al., 2009; Boehmer and Kelley, 2009). If institutions trade as arbitrageurs, they should be able to correct the stock misvaluation caused by the trading of noise traders. Recent empirical evidence also documents institutional herding, which raises some doubts about the impossibility of the synchronization among institutions. Lastly, Battalio and Schultz (2006) argue that during the Dot-com bubble period, investors were able to synthetically short overpriced internet stocks using stock options but they chose not to do so. Short sale

[3]Throughout the paper, I use "institution" and "institutional investor" interchangeably.

constraints may not prevent institutional investors from trading against stock misvaluation because they are the major participants in the derivatives market.

Despite the growth of institutional holdings in the U.S. stock market, it is uncertain whether institutional investors trade against stock misvaluation on average. In this paper, three related research questions are studied. Firstly, I identify stock misvaluation using the factor asset pricing model *alpha* along with two other supplementary methods. Secondly, I investigate whether institutional investors trade against or ride stock misvaluation. Finally, I study which type of institution has a higher tendency to ride stock misvaluation than the others.

Using all the stocks in the U.S. stock market over 1980–2010, I identify stock misvaluation using three methods. The first method to detect stock misvaluation is the rolling regression based on a six-factor model that includes the Fama and French (1993) three factors, the Carhart (1997) momentum factor, the Pastor and Stambaugh (2003) liquidity factor, and the Frazzini and Pedersen (2014) betting against beta factor.[4] The regressions are estimated on a five-year window and rolled over my whole sample period. The factor model *alpha* can be taken as the measure of misvaluation at the stock level. If stock misvaluation always gets corrected due to either exogenous or endogenous reasons, overvalued (undervalued) stocks have negative (positive) abnormal returns in the long run. Therefore stocks with significantly negative (positive) *alpha*s are overvalued (undervalued) during the five-year window.[5]

In the second method, I follow Brunnermeier and Nagel (2004) and assign stocks to quintile or decile portfolios at the end of each month based on their valuation ratios: Price-to-Sales ratio (P/S) or Price-to-Earnings ratio (P/E). Then I calculate equally-weighted

[4]The first five factors are commonly used in both empirical asset pricing and empirical corporate finance literature. I thank the anonymous reviewer's suggestion to include the betting against beta factor in our alpha estimation.

[5]The Fama and French (1993) three-factor model, the Carhart (1997) four-factor model, and the Carhart (1997) four-factor model augmented by the Pastor and Stambaugh (2003) liquidity factor model are checked as well. I also replace five-year rolling windows by three-year rolling windows. My main findings are robust to these specifications.

(EW) and value-weighted (VW) monthly returns of these portfolios, and fit monthly portfolio returns to the six-factor model. The portfolios composed of the highest (lowest) valuation ratio stocks have significantly negative (positive) *alpha*s, suggesting that they are indeed overvalued (undervalued) on average. I also record portfolio five-year rolling *alpha*s, which can be taken as the time-series measurement for the degree of misvaluation.

In the third method, I sort all stocks into quintile portfolios at the end of each month by a dispersion of opinion proxy in the previous month. Then I divide each quintile portfolio further into five groups based on the rank of each stock's short sale constraint proxy in the previous month. Miller (1977) shows that stocks with high dispersion of opinions and high short sale constraints are likely to be overvalued. Boehmer et al. (2006) also find empirical evidence to support Miller's theory. Consistent with these two studies, I find a significantly negative (positive) six-factor model *alpha* for the portfolio with the highest (lowest) dispersion of opinions and the highest (lowest) short sale constraints.

After identifying mispriced stocks and their degree of misvaluation, I investigate the institutional holdings of these mispriced stocks. Following the previous literature, I define institutional holding measures using the Thomson Reuters 13F database. Institutional investors do not appear to underweigh (overweigh) overvalued (undervalued) stocks in their portfolios, using the market portfolio as a benchmark. Intuitively, the negative valuation ratio stocks are more overvalued than stocks with the highest positive valuation ratio. I find that approximately half of the stocks in Brunnermeier and Nagel (2004)'s overvalued portfolio (top quintile P/S stocks) have negative P/E. And institutional investors do not underweigh these negative P/E stocks in their portfolio comparing to the market portfolio.

Similar results are also found when I use the six-factor model *alpha* as the misvaluation measure. The weights of stocks with significantly negative *alpha*s on the aggregate institutional portfolio are very close to their weights on the market portfolio over my whole sample period, suggesting that institutional investors tend to ride stock misvaluation instead of trading against it. Next I compare the institutional holdings of overvalued stocks and undervalued stocks cross-sectionally. Using all the misvaluation measures, the time-series mean of the cross-sectional average of institutional ownership is higher for overvalued stocks than for undervalued stocks. Overall, the tabulated statistics show that institutions do not correct misvaluation since they hold more overvalued stocks than undervalued stocks.

Using multivariate regressions, I show that institutional investors hold more negative *alpha* stocks than positive *alpha* stocks, controlling for other stock characteristics. Additionally, there is a different tendency to invest in overvalued stocks across institution types. I find that investment companies and independent investment advisors have a higher tendency to hold overvalued stocks than other institutions do. Time-series tests further show that institutions increase their holdings of the overvalued stocks when the overvaluation continues to grow. The time-series relationship between the institutional holdings of overpriced portfolios and the overpriced portfolios' rolling *alpha*s is negative, indicating that institutional investors ride stock misvaluation instead of trading against it.

Besides my main results, I find that institutional investor riding stock misvaluation can not be explained by the inflow of funds from individual investors. Institutions do not have a higher tendency to invest in overvalued stocks during the quarters when fund inflows into institutions are higher. And my results are not driven by the Dot-com bubble period and the real estate bubble period either. I find qualitatively similar results for the sample period 1980-1994. Nor are my results industry-specific. I find that institutions overinvest on overvalued stocks in 31 out of the 49 Fama–French industries. The rest of the 18 industries are mainly traditional industries such as Mining and Defense. Institutions show no significant preference for overvalued and undervalued stocks for all of them. Finally, I find weak evidence that institutional investors make a profit by riding stock misvaluation.

In summary, this paper challenges the previous theories that view individual investors as noise traders and institutional investors as rational arbitrageurs. We cannot disregard the role of institutional trading in stock misvaluation and use individual investor's irrationality as the only explanation for stock misvaluation. Kelley and Tetlock (2013) find evidence that the aggregate individual investor is "wise" and that net retail buying can predict future stock returns in their sample from February 2006 to December 2007. Riding stock misvaluation does not mean that institutional investors lose money. On the contrary, institutional investors may gain more profits when they correctly reflect the pulse of stock misvaluation and exit before the price correction.

The remainder of the paper is organized as follows. The next section reviews the related literature. Section 3 develops the hypothesis. Section 4 describes the data sample and variable definitions. Section 5 investigates stock misvaluation and forms overvalued (undervalued) stock portfolios. I also show here whether institutional investors correct stock misvaluation or ride stock misvalation wave. Section 6 includes the results of robustness tests, and Section 7 concludes.

2. Literature Review

Institutions have gradually dominated the U.S. stock market in terms of both market share ownership and trading volume (e.g., Allen, 2001; Gompers and Metrick, 2001; Griffin et al., 2003; Ferreira and Matos, 2008; Kaniel et al., 2008). Because institutional investors and individual investors differ in their demand for stock characteristics and their trading strategies, the growth of institutional ownership in the stock market helps to explain some recent changes in stock return behavior. For example, Kamara (1997) finds that the decrease of Monday seasonality in stock returns can be explained by the increase of the ratio of institutional to individual trading volume. Gompers and Metrick (2001) indicate that the upward shifts on the institutional demand curve combined with institutional investors' preference for large capitalization stocks can partly explain the disappearance of the equity size premium since 1980. To the best of my knowledge, this paper is the first attempt to empirically explore the relationship between institutional holdings and stock misvaluation measures estimated by asset pricing models.

This paper is related to Brunnermeier and Nagel (2004), who study the hedge fund holdings of internet stocks during the Dot-com bubble period and find that hedge funds rode the up-trend of the Dot-com bubble and avoided losses by selling internet stocks before the bubble burst. My paper extends their findings to all U.S. publicly traded stocks and all institutional investors over a sample period 1980-2010. Furthermore, I use asset pricing models to identify mispriced stocks and their degree of misvaluation while Brunnermeier and Nagel (2004) use the top quintile P/S ratio to classify overpriced stocks. Admittedly, any empirical mispricing test is in fact a joint test of stock misvaluation and the efficacy of the model used to define stock fundamental value. To mitigate any concern about the joint hypothesis, I identify stock misvaluation using *alpha* estimated by factor asset pricing models and supplement it by two different metrics. My findings are not sensitive to one-model misspecification.

My work is also related to the theoretical literature on the agency problem of delegated portfolio management. Shleifer and Vishny (1997) indicate that most arbitrageurs are professional investors who manage the fund for other wealthy individual investors, endowments, and pensions. Due to the existence of agency problems, professional investors may forgo some arbitrage opportunities that might incur short-term losses but have long-term positive returns. In their model, the limited effectiveness of professional investors as rational arbitrageurs reduces market efficiency. Among other theoretical works, Allen and Gorton (1993) show that due to information asymmetry, fund managers have incentives to churn asset prices in order to deceive their less informed clients. Fund managers may also intentionally invest in overpriced stocks even though they may lose their clients' money by not exiting before a price correction. Dow and Gorton (1997) argue that conflicts of interest between institutional investors and their clients may force fund managers to engage in uninformed noise trading, because fund managers have incentives to pretend that they are informed traders. Allen and Gale (2000) also find that investors may use borrowed money to invest in risky assets and bid up asset prices because defaulting is always their last resort. Goldman and Slezak (2003) indicate that fund managers lose the incentive to trade on long-term information, when it takes longer to reveal their private information than their tenure. This may cause rational prolonged stock mispricing. Abreu and Brunnermeier (2002, 2003) argue that the synchronization risk delays rational arbitrage and the competition among institutional investors may force fund managers to invest in overvalued assets with high past returns. This "keeping up with the Joneses" trading behavior leads to excess volatility and market fragility. Hong et al. (2008) show that because of future career concerns, even well-intentioned professional investment advisors may overstate their estimates of new technology stock returns as a positive signal so that more investors will follow them in the future.

Besides the above theoretical models, empirical studies show mixed evidence for the role of institutional investors in stock misvaluation. Lakonishok et al. (1992) study 768 tax-exempt (mostly pension) funds, and find little evidence that these funds act as positive-feedback traders or follow each other into and out of the same stocks. But Greenwood and Nagel (2009) find that younger mutual fund managers invest more in technology stocks than their older colleagues. They argue that the growth of inexperienced investors' participation on the stock market could have been a driving factor in the Dot-com bubble. Recent studies on institutional momentum trading and herding (e.g., Grinblatt et al., 1995; Wermers, 1999; Badrinath and Wahal, 2002; Sias, 2004; Sias et al., 2006; Sias, 2007) also suggest that institutional trading may lead to stock misvaluation. Grinblatt et al. (1995) also find that institutions engaging in momentum trading perform better than other institutions, indicating an incentive for institutional investors to ride stock misvaluation.

3. Hypothesis

Motivated by the growth of institutional ownership in the stock market, previous literature has studied the role of institutions in stock market efficiency. The competing theories and empirical evidence can be categorized into three groups: rational arbitrageur, destabilizing trend chaser, and neutral on average.

3.1. Rational Arbitrageur

According to the traditional view, institutional investors are rational arbitrageurs in the stock market. They explore stock misvaluation opportunities and drive stock prices back to their intrinsic value. In general, institutions are experienced investors and specialize in trading stocks in certain industries. Compared with individual investors, institutions are better informed and more resourceful. In addition, institutions have economies of scale in aggregate trading and utilizing collective financial information, which greatly lower their transaction costs. The traditional view predicts that institutions are more likely to sell overvalued stocks and to buy undervalued stocks.

3.2. Trend Chaser

An opposite view on institutional investors is that they chase stock momentum and ride stock misvaluation. Institutional investors have much larger holdings than individual investors. If institutions herd, their trading has a much stronger effect on stock prices than the trading of individual investors. However, institutional herding does not necessarily destabilize stock prices unless they ride stock misvaluation. When institutional investors ignore stock fundamental value and just mimic each other's trades due to information asymmetry and agency problems, for example, information cascades, fads, and reputational herding, the institutional herding will push stock prices away from the fundamentals.

Previous empirical studies also document momentum trading initiated by institutional investors. Following positive feedback trading strategies, institutional investors may chase stock return trends and buy (sell) stocks after their prices rise (fall). Kaniel et al. (2008) find that institutions are positive feedback traders on average, while individual investors tend to trade as negative feedback traders and provide liquidity for institutional demand. Furthermore, institutional investors often use stop loss orders, which may force them to sell stocks after a certain level of losses, regardless of their expectation of stock future returns. Before the price correction, institutional investors are better off selling out near the peak or buying near the bottom than just trading against the trend. Even though in the long run institutions drive stock prices back to fundamentals, trend chasing by institutional investors still destabilizes stock prices.

3.3. Neutral on Average

The third view on institutional investors is that they are just neutral on average. Because institutions are heterogenous, their trades may offset each other. As long as the majority institutional demand and supply cancel out, institutional trading does not affect stock return characteristics. Therefore, there is no significant relationship between institutional trading and stock misvaluation.

Based on these three views, I state my three main hypothesis:

- ***Hypothesis (H0):*** *Institutional investors are rational arbitrageurs on average. Their aggregate trading drives stock prices back to fundamentals.*
- ***Hypothesis (H1a):*** *Institutional investors are trend chasers on average. They ride stock misvaluation instead of trading against it.*
- ***Hypothesis (H1a):*** *Institutional investors trade with each other. Their orders offset each other and have no net effect on stock prices.*

4. Data

In this section, I briefly introduce my data sources and the definitions of institutional ownership variables. For detailed information, please refer to the Appendix.

4.1. Data sources

My sample is collected from several data sources: (i) The institutional investor stock holdings and institution types are from the Thomson Reuters CDA/Spectrum 13F database. (ii) Stock prices, share outstandings, and dividends are from the Center for

Research in Security Prices (CRSP) daily and monthly tapes for all NYSE, AMEX, and NASDAQ stocks. (iii) Firms' accounting data are collected from the CRSP/COMPUSTAT merged database. Stock short interest and S&P 500 constitutes are collected from the COMPUSTAT monthly file. (iv) Data on financial analysts' earnings forecasts are retrieved from the Institutional Brokers Estimate System (I/B/E/S). (v) Data for the Fama–French three factors, the Carhart momentum factor, and the Pastor–Stambaugh liquidity factor are from the Wharton Research Data Services (WRDS). (vi) Data for the betting against beta factor is downloaded from Lasse H. Pedersen's website. (vii) The Fama–French 49 industry classification is downloaded from Kenneth R. French's website. Because institutional ownership data in CDA/Spectrum can only be traced from 1980, my main sample period is from 1980 to 2010.

4.2. Institutional ownership variable definitions

Next I describe how institutional ownership measurements are constructed in this paper. Following the previous literature on institutional investors, I define the institutional holding measure at the end of quarter t and their herding measures over quarter t, respectively.

Measurement 1:

$$IO_{i,t} = \sum_{j=1}^{N} \frac{\text{Shares}_{j,i,t}}{\text{Shares Outstanding}_{i,t}}$$

Following Gompers and Metrick (2001), I define my main institutional holding measurement $IO_{i,t}$ as the percentage level of institutional ownership of stock i at the end of quarter t. N is the number of institutional investors who hold stock i at the end of quarter t. $Shares_{j,i,t}$ is the number of stock i shares held by institution j at the end of quarter t. Shares $\text{Outstanding}_{i,t}$ is the total shares outstanding of stock i at the end of quarter t. If stock i is not held by any institutions at the end of quarter t, then $IO_{i,t}$ is equal to zero.[6] $IO_{i,t}$ is a cumulative institutional holding measure which is determined by the aggregate institutional trading before the end of quarter t. The cross-sectional variation of $IO_{i,t}$ indicates institutional investors' preference for stock characteristics. The time series of $IO_{i,t}$ reveals the change of institutional holdings of stock i with respect to the changes of stock i's characteristics.[7]

Measurement 2:

$$HM_{i,t} = |p_{i,t} - E[p_{i,t}]| - E[|p_{i,t} - E[p_{i,t}]|]$$

$$BHM_{i,t} = HM_{i,t}|p_{i,t} > E[p_{i,t}]$$

$$SHM_{i,t} = HM_{i,t}|p_{i,t} < E[p_{i,t}]$$

$$p_{i,t} = \frac{\text{Number of Institutions Buying}_{i,t}}{\text{Number of Institutions Buying}_{i,t} + \text{Number of Institutions Selling}_{i,t}}$$

Lakonishok et al. (1992) and Wermers (1999) use $HM_{i,t}$ to investigate institutional investor herding. This measure captures whether a disproportionate number of institutions are buying or selling stock i over quarter t. $p_{i,t}$ is defined as the proportion of active traders in stock i who are buyers. $E[p_{i,t}]$ is the expected proportion of institution buying stock i over quarter t relative to the total number of active institutions. It is estimated as the ratio of the number of institutional purchases to the total number of institutional active trades at time t. $E[|p_{i,t} - E[p_{i,t}]|]$ is an adjustment factor which allows for random variation around the expected proportion of buyers under the null hypothesis of independent trading decisions by institutions.[8] $HM_{i,t}$ captures the tendency of a given subgroup of institutions

[6]Holdings that are less than $200,000 or 10,000 shares will not be reported. So there is a small downward bias to $IO_{i,t}$ measurement, especially for small stocks. And we would expect a weak positive relationship between IO and size due to this bias alone.

[7]In the unreported tests, other institutional trading measures such as the net dollar amount of institutional purchase divided by the total dollar amount of institutional trading for stock i over quarter t (Lakonishok et al., 1992); standardized shares purchased by institutions (Sias, 2004); and the change in the number of institutions holding stock i over quarter t (Jiang, 2010) are studied. Qualitatively similar results are generated.

[8]Subtracting this adjustment factor addresses the concern that stocks that are not actively traded lead to a positive difference between $p_{i,t}$ and $E[p_{i,t}]$ even if each institution trades independently. The adjustment factor decreases with the number of institutions trading in the stock. It is easy to calculate the

to trade stock i over quarter t together and in the same direction, which is more frequent than would be expected by trading randomly and independently.

Based on $HM_{i,t}$, I define two conditional institution trading measures: $BHM_{i,t}$ and $SHM_{i,t}$ (Grinblatt et al., 1995; Wermers, 1999). $BHM_{i,t}$ ($SHM_{i,t}$) is the conditional buy-herding (sell-herding) measurement for stock i at the end of quarter t.[9] These two conditional measures separate institution herding into stocks from herding out of stocks. A high $BHM_{i,t}$ ($SHM_{i,t}$) suggests that the number of net buyers (sellers) of stock i over quarter t is greater than the expected average.

5. Main results

5.1. The rise of institutional ownership in the U.S. stock market

Previous literature on institutional investors documents that the institutional ownership of stock market increases gradually and has a positive time trend. Figure 1 displays the time-series plots of institutional holdings and the number of institutions at the end of every year from 1980 to 2010. Figure 1.1 presents the institutional holding scope relative to the total stock market value. Following Gompers and Metrick (2001), the percentages of market value held by all institutions, the 100 largest institutions, the 10 largest institutions, and the largest institution covered in the Thomson Reuters 13F database at the end of each year are presented. Institutional holdings have increased steadily over my sample period and the growth in the largest institutions accounted for most of the total institutional holding growth. In December 1980, the largest 100 institutions owned slightly above 20% of the stock market. In December 2005, the market share of the top 100 institutional holdings exceeded 50% of the total stock market value. Figure 1.2 plots

adjustment factor numerically given that the number of institutional buying follows a Binomial distribution with probability $E[p_{i,t}]$ of success and the total number of active institutions. Please find the detailed information about this measure in Lakonishok et al. (1992) and Wermers (1999).

[9] The adjustment factors in $BHM_{i,t}$ and $SHM_{i,t}$ are recalculated conditional on $p_{i,t} > E[p_{i,t}]$ or $p_{i,t} < E[p_{i,t}]$. That is, I separate all stock-quarters into a buy-herding subsample or a sell-herding subsample, then calculate $BHM_{i,t}$ and $SHM_{i,t}$ separately in two subsamples.

institutional holdings by five institution types: Bank, Insurance Company, Investment Company (mutual fund), Independent Investment Advisor (including hedge fund), and All Others (endowment, pension, and foundation). From 1980 to 1997, investment companies and independent investment advisors significantly increased their holdings relative to the other three types of institutions.[10] Figure 1.3 tracks the number of institutions in my sample. The total number of institutions has quintupled and recently approached 3,000.

Table 1 reports the summary statistics for institutional holdings and stocks covered in my sample. Panel A of Table 1 shows that the total stock market value grew more than 10 times from 1980 to 2010. During the same time period, the dollar amount of institutional holdings grew approximately 20 times, from $460 billion to $10,058 billion. As a result, institutional holdings accounted for almost 70% of total stock market value in December 2010, nearly doubled from 35% in December 1980. After 1995 institutions controlled more than half of the stock market, and in recent years they eventually became the dominating participants. Panel B of Table 1 reports the mean numbers of institutions and stocks covered in my sample. On average, my sample contains 4,604 stocks and 1,426 institutions each quarter. The time-series mean of the cross-sectional average of institutional holdings indicates that a representative institution holds 219 stocks in a portfolio with $2.5 billion market value. Panel C of Table 1 reports the summary statistics for the number of institutional owners per stock at the end of each year. All the stocks included in Panel C have at least one institutional owner. The average number of institutional owners for one stock has increased from 27 in December 1980 to 156 in December 2010.

Overall, institutional investors have achieved a domination of the U.S. stock market over my sample period. The largest institutions exercise discretionary control of most institutional holdings. It is interesting to investigate the institutional holdings of mispriced stocks.

[10]Because institution type codes are not accurate after 1998 in the Thomson Reuters 13F database, the time span of Figure 1.2 is only between 1980 and 1997. And the sample period for all the empirical results about institutional investor types is between 1980 and 1997.

5.2. Three measures of stock misvaluation

The efficient market theory suggests that no investor can consistently achieve risk adjusted returns above the average market returns, given all the information available at the time of investment. Grossman and Stiglitz (1980) recognize that if the stock market is perfectly efficient, then investors would lose the incentive to collect and analyze information. They argue that stock market frictions, such as transaction costs and asymmetric information, lead to stock market inefficiency. Recent research on stock overvaluation also indicates that the aggregate effect of differences of opinions and short sale constraints may cause stock overvaluation. In this paper, I study the institutional holdings of misvalued stocks. So it is important to identify the stock candidates that are the most likely to be overvalued or undervalued during my sample period. Admittedly, stock fundamental value is never observed by investors and any test of misvaluation suffers from the joint hypothesis problem that either the asset pricing model is incorrect or the stock is mispriced. To mitigate the concern of such a joint hypothesis, three generalized metrics extensively used in the previous literature to identify stock misvaluation are applied in this paper.

5.2.1. Factor asset pricing model *alpha*

The first method is to fit individual stock monthly returns to factor asset pricing models directly. Stocks with significantly negative *alpha*s are overvalued and stocks with significantly positive *alpha*s are undervalued. I use the six-factor model that augments the Fama and French (1993) three-factor model by the Carhart (1997) momentum factor, the Pastor and Stambaugh (2003) liquidity factor, and the Frazzini and Pedersen (2014) betting against beta factor in my main analysis:

$$\begin{aligned} R_{p,t} - R_{f,t} =& \alpha_p + \beta_p(R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + u_p UMD_t + l_p L_t \\ &+ b_p BAB_t + \epsilon_{p,t} \end{aligned} \tag{1}$$

The first five factors have been extensively used in the previous empirical asset pricing literature. Sias (1996) documents a positive contemporaneous relationship between institutional ownership level and the stock return volatility. To account for the volatility bias and volatility premium (e.g., Asness et al., 2014; Frazzini and Pedersen, 2014), I also include the betting against beta factor in the factor model. Both five-year and three-year rolling windows are checked over the sample period from January 1980 to December 2010.

Table 2 reports the summary statistics for the number of nonzero *alpha* stocks. Panel A shows that on average there are 256 stocks with significantly negative *alpha* and 433 stocks with significantly positive *alpha* if monthly stock returns are fitted to the six-factor model with a five-year rolling window. And Panel B shows that on average there are 377 stocks with significantly negative *alpha* and 461 stocks with significantly positive *alpha* if monthly stock returns are fitted to the six-factor model with a three-year rolling window. The significance level I choose is 10% at each tail.

5.2.2. Valuation ratios

Brunnermeier and Nagel (2004) and Greenwood and Nagel (2009) use the ratio of price-to-sales (P/S) to identify overvalued internet stocks during the Dot-com bubble period. They find that the P/S ratio captures technology industry stocks with an extreme valuation. Following these two studies, I use the P/S and the ratio of price-to-earnings (P/E) as the second method to identify misvalued stocks.[11] Each month, all stocks are sorted into quintile or decile portfolios based on the level of valuation ratios at the end of the previous month. Stocks in the top (bottom) quintile or decile portfolios have the highest (lowest) valuation ratios and are most likely to be overvalued (undervalued). Both the equally-weighted (EW) and value-weighted (VW) monthly returns for these portfolios

[11] The P/S ratio is a valuation metric for stocks. It is calculated by dividing the company's market cap by its total sales over a 12-month period. The P/E ratio is a ratio for valuing a company that measures its current share price relative to its per-share earnings. In unreported tests, I also check the other three widely used valuation ratios: the Price-to-Book ratio (P/B); the Price-to-Cash Flow ratio (P/CF); and the Price-to-Earnings Before Interest, Taxes, Depreciation and Amortization ($P/EBITDA$). The results are similar to P/E.

are calculated. Then I estimate the six-factor model *alpha*s for these portfolios.[12]

Table 3 presents the quintile and decile portfolio *alpha*s, estimated by the six-factor model over my sample period. The first row of Panel A shows that for both P/S and P/E, the six-factor model *alpha*s are all significantly negative for top quintile portfolios, indicating that the stocks with the highest valuation ratios are indeed overvalued. The second row of Panel A shows that, for P/S, the six-factor model *alpha*s are significantly positive for bottom quintile portfolios, suggesting that stocks with the lowest P/S are indeed undervalued. However, *alpha*s for bottom quintile portfolios sorted by P/E are also significantly negative. These results are mainly driven by the fact that firms with negative earnings are included in the bottom quintile portfolio, but stocks with negative valuation ratios are more likely to be overvalued than stocks with the highest positive valuation ratios.

I use two methods to mitigate the negative valuation ratio issue. The first method is to exclude the observations with negative P/E ratios from the sample. The third and fourth rows of Panel A report the *alpha*s of Quintile 5 and Quintile 1 portfolios formed by only sorting stocks with only positive P/E ratios. The alternative method is to adjust the negative valuation ratios so that stocks with negative valuation ratios are assigned to top valuation ratio portfolios. I choose the negative earnings yield (E/Y ratio).[13] The fifth and sixth rows of Panel A report the *alpha*s of Quintile 5 and Quintile 1 portfolios formed by sorting stocks according to their negative earnings yields (E/P). Using these two alternative methods to sort stocks, I find that Quintile 5 (1) portfolios have significantly negative (positive) *alpha*s, suggesting that stocks in Quintile 5 (1) portfolio are overvalued (undervalued).

[12]There is a general agreement by most researchers that internet stocks in the Dot-com bubble period were overvalued. So it is reasonable for Brunnermeier and Nagel (2004) to use a high P/S ratio to identify overpriced stocks during this period. However, whether the high P/S ratio stocks over my sample period are overvalued remains uncertain. The factor model *alpha* is a more rigorous misvaluation measurement than the valuation ratios.

[13]I thank the anonymous reviewer for this suggestion. I add a negative sign to the earnings yield so that overvalued stocks can be sorted into the top quintile or decile portfolios.

Panel B of Table 3 show the *alpha*s of ten decile portfolios formed by sorting P/S and adjusted P/E. The results indicate a clear pattern that estimated six-factor model *alpha*s decrease almost monotonically from significantly positive in Decile 1 portfolios to significantly negative in Decile 10 portfolios.

5.2.3. Differences of opinions and short sale constraints

Miller (1977) shows that heterogenous expectations across investors may lead to stock overvaluation if short sale constraints on overvalued stocks prevent investors with negative information from getting access to the stock market. Motivated by Miller's theory, both theoretical (e.g., Chen et al., 2002; Scheinkman and Xiong, 2003) and empirical studies (e.g., Diether et al., 2002; Lamont and Thaler, 2003; Ofek and Richardson, 2003; Boehmer et al., 2006) conclude that differences of investor opinions and short sale constraints can together cause stock overvaluation or bubbles. Therefore, my third method to identify overvalued stocks is a two-dimensional criterion including one proxy variable for differences of opinions and one proxy variable for short sale constraints.

The ideal measure of stock short sale constraints is the stock short sale rebate rate which is not available in public database so far (Jones and Lamont, 2002; Boehmer et al., 2006).[14] However Boehmer et al. (2006) document a positive relationship between the short sale rebate fee and the short interest (SI) for the same stocks.[15] So I use SI as the proxy variable for short sale constraints in my main analysis. The arguably best proxy for differences in investor opinions is the standard deviation of the I/B/E/S analyst earnings forecast (Diether et al., 2002). But this proxy is only available for stocks covered by at least two analysts, which may cause sample bias against small firm stocks with little analyst

[14] Jones and Lamont (2002) argue that the rebate rate measures the price of short selling a stock that equilibrates supply and demand in the borrowing market. The higher the short sale rebate rate, the more expensive to short sell the corresponding stock.

[15] Boehmer et al. (2006) also use the stock option status as a supplementary variable to estimate the stock short sale rebate fee. The option status data in my sample is only available after 1998, so I only include the option status variable in my robustness tests. Boehmer et al. (2006) find that SI has significantly higher explanatory power than the option status variable, and excluding the option status variable does not qualitatively affect my results.

coverage. Following Boehmer et al. (2006), I use the following regression model to estimate a unitary $Dispersion_{i,t}$ proxy variable:

$$
\begin{aligned}
Dispersion_{i,t} = {} & Constant + \beta_1 SIGMA_{i,t} + \beta_2 SIGMA^2_{i,t} + \beta_3 TURNOVER_{i,t} \\
& + \beta_4 TURNOVER^2_{i,t} + \epsilon_{i,t}
\end{aligned}
\tag{2}
$$

where $Dispersion_{i,t}$ is the standard deviation of the I/B/E/S analyst earnings forecast normalized by the mean of the earnings forecast. $SIGMA_{i,t}$ is the standard deviation of the error term in the $CAPM$ model, estimated over a three-month window for stock i's daily returns before time t; and $TURNOVER_{i,t}$ is the trading volume normalized by the shares outstanding of stock i over the previous three months. Regression (2) is estimated for stocks covered by at least two analysts. Then the regression coefficients are used to calculate the $Dispersion_{i,t}$ proxy for all the stocks with available $SIGMA_{i,t}$ and $TURNOVER_{i,t}$ data.

Due to the non-stationarity in the $SIGMA_{i,t}$ and $TURNOVER_{i,t}$, I follow Boehmer et al. (2006) and sort all the stocks into twenty groups by their actual $Dispersion_{i,t}$, $SIGMA_{i,t}$, and $TURNOVER_{i,t}$ value at each month. Then I use the rank of the group to which stock i is assigned as the value of the variables in regression (2). So all $Dispersion_{i,t}$, $SIGMA_{i,t}$, and $TURNOVER_{i,t}$ take discrete values from 1 to 20 in regression (2). The actual values of the variables are also tested in regression (2) as a robustness check.

Next I sort all stocks by the estimated $Dispersion_{i,t}$ proxy into five quintile portfolios at each month. I further divide each quintile portfolio into five subgroups by using $SI_{i,t}$. The stocks in the portfolio Quintile 5 & Quintile 5 (Q5 & Q5) with the highest $Dispersion_{i,t}$ and $SI_{i,t}$ are most likely to be overvalued. Then I calculate monthly returns for the portfolio Q5 & Q5 and fit the returns to the six-factor model. For comparison, I repeat the same analysis for portfolio Quintile 1 & Quintile 1 (Q1 & Q1) with the lowest $Dispersion_{i,t}$ and $SI_{i,t}$ ranks. Both EW and VW portfolio returns are tested. And because the number of stocks in the portfolio varies from month to month, I use both ordinary least squares (OLS) and weighted least squares (WLS) in my analysis. The weights in the WLS regressions are the number of stocks in portfolios every month.

Table 4 shows that the six-factor model *alpha*s for portfolio Q5 & Q5 are all significantly negative, indicating that the stocks with the highest $Dispersion_{i,t}$ and $SI_{i,t}$ are indeed overvalued on average. The five factor model *alpha*s for portfolio Q1 & Q1 are significantly positive if the EW monthly returns are tested, suggesting that stocks with the lowest $Dispersion_{i,t}$ and $SI_{i,t}$ are undervalued on average. However the six-factor model *alpha*s for portfolio Q1 & Q1 are not significant if the VW monthly returns are used, suggesting that the undervalued stocks in Q1 & Q1 portfolios are mostly small firm stocks.

In summary, I use three methods to identify misvalued stocks in my sample. These three methods together provide robust evidence that stock misvaluation persists during my sample period, despite the fact that institutional investors have controlled the major portion of the stock market. In the next section, I will investigate the institutional holdings of these misvalued stocks.

5.3. Institutional holdings of misvalued stocks: Preliminary results

In this section, I present the preliminary statistics of institutional holdings of misvalued stocks. If institutional investors act as arbitrageurs, they should buy undervalued stocks and sell overvalued stocks. As a result, institutional investors should hold fewer overvalued stocks and more undervalued stocks using the market portfolio as the benchmark.

5.3.1. Institutional ownership and stock *alpha*

I first form portfolios using *alpha*s estimated by the six-factor model with rolling five-year windows. Each month, the overvalued portfolio includes all the stocks with significantly (10%) negative *alpha* and the undervalued portfolio includes all the stocks with significantly (10%) positive *alpha*. In Figure 2, I compare the weights of these misvalued stocks on the aggregate institutional investor portfolio to the weights of these misvalued stocks on the market portfolio. The top panel of Figure 2.1 shows that institutional investors invest more (less) on the significantly negative *alpha* stocks when the weights of these overvalued stocks in the market portfolio increase (decrease). The bottom panel of Figure 2.1 shows the difference between the weights of overvalued stocks in the institutional investor portfolio and the weights of overvalued stocks in the market portfolio. For most of the time periods, this difference is positive. There is no evidence that the aggregate institutional investor underweighs these overvalued stocks in her portfolio using the market portfolio as a benchmark.

Similarly, the top panel of Figure 2.2 shows that institutional investors do not overweigh undervalued stocks in their portfolio relative to the market portfolio either. The bottom panel of Figure 2.2 shows the difference between the weights of undervalued stocks in the institutional investor portfolio and the weights of undervalued stocks in the market portfolio. For only about half of the sample period, institutional investors hold more undervalued stocks in their portfolio than the market does in the market portfolio. The maximum difference is slightly above 0.05%, much lower than the weight levels of undervalued stocks in both institutional investor portfolio and the market portfolio.

Next, I compare the institutional holdings of stocks with significantly positive *alpha* to institutional holdings of stocks with significantly negative *alpha*. The previous literature shows that institutional ownership increases with firm size and that large firm stocks have outperformed small firm stocks since 1980 (Gompers and Metrick, 2001). Therefore I divide all stocks into 5 quintile groups by their market value at each quarter. In each quintile group, I calculate the time-series mean of the cross-sectional average of institutional ownership IO for significantly positive *alpha* stocks and significantly negative *alpha* stocks. *Alpha*s are estimated by using the six-factor model with rolling five-year windows and rolling three-year windows. Panel A of Table 5 shows that institutional investors hold more significantly negative *alpha* (overvalued) stocks than significantly positive *alpha* (undervalued) stocks in Quintile 1–3 groups. The mean difference tests show that IOs are significantly different at 1% between positive *alpha* and negative *alpha* groups. Only in the Quintile 5, that includes the largest stocks, are the results reversed.

5.3.2. Institutional ownership and stock valuation ratios

Following Brunnermeier and Nagel (2004), I treat all institutions as one giant institutional investor. Then I assign stocks to ten decile portfolios by P/S, P/E with only positive value, respectively. The weights of the top and bottom decile valuation ratio portfolios on the aggregate institutional investor portfolio are derived at the end of each quarter. As a benchmark, the quarterly weights of the top and bottom decile valuation ratio portfolios on the market portfolio are also calculated. As shown in Figure 3.1 and Figure 3.2, the red dotted lines represent the time-series weights of top or bottom decile portfolio stocks on the aggregate institutional investor's portfolio. And the blue solid lines represent the time-series weights of top or bottom decile portfolio stocks on the market portfolio. If the aggregate institutional investor keeps buying undervalued stocks and selling overvalued stocks, the red dotted lines should be above (below) the blue solid lines with a significant gap for all bottom (top) decile portfolio figures.

However, the graphs on the left column of Figure 3.1 and Figure 3.2 show that the aggregate institutional investor does not overweigh undervalued stocks in its portfolio compared to the market portfolio. The graphs on the right column of Figure 3.1 and Figure 3.2 show that the aggregate institutional investor does not underweigh overvalued stocks in its portfolios compared to the market portfolio either. In fact, both weight curves move concurrently over time in Figure 3.1 and 3.2. When overvalued stock portfolio weights in the market portfolio increase, the aggregate institutional investor also increases the weights of overvalued stocks in its portfolio.

Brunnermeier and Nagel (2004) find that hedge funds generally overweigh technology stocks in their portfolios and most of the technology stocks do not even have positive earnings during the Dot-com bubble period. Brunnermeier and Nagel (2004) use the top quintile P/S to classify overpriced internet stocks. During their sample period from March 1998 to December 2000, 53% of top quintile P/S stocks have negative P/E, suggesting that Brunnermeier and Nagel (2004)'s findings may be mainly driven by the negative valuation ratio stocks. At the end of each quarter, I sort all negative P/E stocks into one portfolio. The ratios of the market value of negative P/E stock portfolio to the market portfolio value are calculated at quarterly end as benchmarks. The ratios of the market value of negative P/E stock portfolio held by institutions to the market value of aggregate institutional investors' portfolio are also calculated at quarterly end. Figure 3.3 shows that over my sample period 1980-2010, there is no evidence that institutional investors underweigh negative P/E stocks in their portfolio comparing to the market portfolio.

The preliminary summary statistics also show similar results. Panel B of Table 5 presents the time-series mean of the cross-sectional average of institutional holding measurements on portfolios formed by valuation ratios. Comparing the institutional holding measurements on top quintile valuation ratio portfolios with bottom quintile valuation ratio portfolios, I find no evidence that institutions hold more undervalued stocks than overvalued stocks on average. The t-tests that IOs are lower in overvalued portfolios ($Q5$) than in undervalued portfolios (Q1) are not significant.[16]

5.3.3. Institutional ownership of misvalued stocks identified by dispersion of opinions and short sale constraints

In Panel C of Table 5, I present the time-series mean of the cross-sectional average of institutional ownership on stock portfolios formed by the dispersion of opinion proxy and short sale constraint proxy. My previous tests have shown that stocks with the highest (lowest) dispersion of opinion and the highest (lowest) short sale constraints tend to be overvalued. But I do not find evidence that institutional investors hold fewer shares in portfolio D10 & D10 than D1 & D1. D10 & D10 represents the top decile dispersion

[16] In unreported tests, I use the cross-sectional median of institutional holding measures and find qualitatively similar results.

of opinions and top decile short sale constraints. D1 & D1 represents the bottom decile dispersion of opinions and bottom decile short sale constraints.

In summary, the preliminary summary statistics by tabulation suggest that there is no evidence of institutions putting more weights on undervalued stocks than overvalued stocks. However, Gompers and Metrick (2001) suggest that institutional investors prefer to hold stocks with certain characteristics. The preliminary results are not conclusive. It is necessary to test the relationship between institutional ownership and stock misvaluation measures using multivariate analysis.

5.4. Institutional holdings and stock misvaluation: Multivariate analysis

In this section, I investigate the relationship between institutional holdings and individual stock misvaluation using multivariate regressions. At the end of each quarter over my sample 1980–2010, I estimate the following cross-sectional regression:

$$IO_i = C_i + \beta_\alpha alpha_i + \beta_i X_i + \epsilon_i \tag{3}$$

where IO_i is the percentage of institutional ownership on stock i, and $alpha_i$ is estimated by the six-factor model with rolling five-year windows.[17] X_i is the vector of stock characteristics used in Gompers and Metrick (2001), including $Size$, B/M, $DividendYield$, $Price$, previous two-year monthly return $Volatility$, $Momentum1$ for the past three months, $Momentum2$ for the nine-month period before the past three months, share $Turnover$, and $S\&P$ 500 dummy.[18] To account for heteroskedastic errors, I use White robust error estimators for the standard error estimations in all regressions (White, 1980).

In regression (3), $alpha_i$ represents a measure of stock misvaluation over the past five

[17] My results are robust for $alpha_i$ estimated by the six-factor model with rolling three-year windows and the four-factor model with five-year rolling windows. In the rest of this paper, I will only report the results based on $alpha_i$ estimated by the six-factor model with rolling five-year windows.

[18] See detailed definition in Appendix A.2.3.

years. When the dependent variable is institutional ownership IO_i, a cumulative measure of institutional ownership on misvalued stocks, regression (3) investigates the long-term relationship between institutional holdings and stock misvaluation. When the dependent variable is BHM_i or SHM_i, regression 3 investigates institutional investors' quarterly response to the level of stock misvaluation over the past five years.

5.4.1. Cross-sectional regressions by quarter

I first estimate cross-sectional regressions separately for each quarter over my whole sample period. Because the regression coefficients are not independent across quarters, I do not report any other time-series statistics other than the coefficient average.

Panel A of Table 6 reports average regression coefficients, the number of positive and negative coefficients, and the number of significant (5%) positive or negative coefficients for all the quarterly OLS regression (3). The dependent variable is institutional ownership IO and the independent variable $alpha_i$ is the significant $alpha$ dummy, which is equal to 1 (–1) if the actual $alpha$ is positive (negative) and significant at 10%. The results show that there is a consistently negative relationship between institutional ownership and stock $alpha$. For 86 out of 105 quarters, the relationship between institutional ownership and stock $alpha$ is negative; and 61 out of 86 negative coefficients are significant at the 5% level.

In Panel B and Panel C of Table 6, I change the dependent variable into institutional buy-herding measure BHM and institutional sell-herding measure SHM. The results show that institutional investors are more likely to herd into (out of) stocks with significantly negative (positive) $alpha$s.[19]

[19] In unreported analysis, I use different $alpha$ measurements such as actual value of significant $alpha$, significant actual $alpha$ lag by 1 quarter, $alpha$ dummy for all stock observations including statistically insignificant $alpha$, and actual stock $alpha$ for all stock observations. Qualitatively similar results have been found.

5.4.2. Pooled regressions with double-clustered standard errors by firm and quarter

The residual terms in regression (3) usually have time-series autocorrelation over long horizons. Therefore, I adjust the standard errors for cross-sectional and time-series correlation in the residual terms by a pooled regression with two-way (firm and quarter) clustering of standard errors (Petersen, 2009).

Panel A of Table 7 reports the results of pooled regressions in which the dependent variable is institutional ownership IO. In column (1), the independent variable $alpha_i$ is the significant *alpha* dummy, which is equal to 1 (-1) if the actual *alpha* is positive (negative) and significant at 10%. The coefficient of the significant *alpha* dummy is -0.031 and significant at 1%, suggesting that the institutional ownership is 6.2% higher in overvalued stocks than undervalued stocks controlling for other stock characteristics. In column (2) of Panel A, the independent variable $alpha_i$ is the actual value of significant *alpha* estimated by the six-factor model with five-year rolling windows. The coefficient of actual *alpha* is -0.79 and significant at 1%, suggesting that the institutional ownership on misvalued stocks increases by 0.79% when the actual *alpha* decreases by 1%. From column (3) to column (5), the independent variables $alpha_i$ are the significant actual *alpha* lagged by 1 quarter, the dummy *alpha* for all observations including the statistically insignificant *alpha*, and the actual *alpha* for all observations. All the coefficients of *alpha* variables are negative and statistically significant at 1%. These results show that institutional holdings are higher in overvalued stocks than undervalued stocks cross-sectionally, controlling for other stock characteristics.[20]

In Panel B of Table 7, the dependent variables are the institutional buy-herding measure BHM. All five coefficients of the *alpha* variables in Panel B are negative and significant above the 10% level. These suggest that for all the stocks which institutions buy, the herding intensity on overvalued stocks is higher than on undervalued stocks,

[20] In unreported tests, I get similar results when I use the six-factor three-year rolling *alpha*s and five-factor five-year rolling *alpha*s.

controlling for other stock characteristics. In Panel C of Table 7, the dependent variables are the institutional sell-herding measure SHM. All five coefficients of the *alpha* variables are positive and three are significant above the 10% level. The coefficients for the actual significant *alpha* in column (2) and *alpha* lag in column (3) are positive but not significant. These results indicate that for all the stocks which institutions sell, the herding intensity on undervalued stocks is higher than on overvalued stocks, controlling for other stock characteristics.

In Table 8, I show that the cross-sectional relationship between institutional holdings and stock *alpha*s differs across institution types. Following Kamara et al. (2008), I separate all institutional investors into three groups: banks and insurance companies, investment companies and independent investment advisors, and all others (pension funds, university endowments, foundations) over the sample period 1980–1997. Among these three groups, investment companies and independent advisors trade the most frequently and are the least risk averse. Therefore, it is expected that investment companies and independent advisors are most likely to ride stock misvaluation. Pension funds, university endowments, and foundations are the most risk averse among these three groups due to strict regulation and laws. Therefore, they tend to be the long-term investors and are least likely ride stock overvaluation. The results in Table 8 show that all the coefficients on *alpha*s are significantly negative, suggesting that all three institution groups ride stock overvaluation. Consistent with my expectations, the negative coefficients of *alpha*s for investment firms and independent investment companies are lower than for the other two institution groups. The coefficients of *alpha*s for all other groups are the smallest in absolute value, which indicates that institutions in all other groups have the least tendency to ride stock overvaluation. During the Dot-com bubble period, almost all institutions increased their exposure to overvalued internet stocks. But due to the restrictions on investment class and riskiness, pension funds, university endowments, and foundations invested relatively less in the overvalued internet stocks than institutions in the other two groups. Ofek and Richardson (2003) find evidence that pension funds underweigh internet stocks in their portfolios more than the other investors.

5.5. Time-series relationship between institutional holdings and stock misvaluation

I next investigate the time-series relationship between institutional holdings and the degree of stock overvaluation. I have already shown that the top decile and quintile valuation ratio portfolios are overvalued. In the following tests, I focus on the VW, P/S top quintile portfolio. At each quarter, I record the time-series degree of overvaluation on the portfolio: $alpha_t$ estimated by the six-factor model with rolling five-year windows. The average institutional ownership measure IO on the portfolio is also recorded.

Because institutional holdings increase over time, I use the following regression to test whether the time series of IO_t and $alpha_t$ are stationary and whether they have a time trend (Dickey and Fuller, 1979):

$$Y_t - Y_{t-1} = C + (\lambda - 1)Y_{t-1} + \beta T + \epsilon_i \tag{4}$$

Panel A of Table 9 shows that the coefficients of lag IO_t and $alpha_t$ are both significantly different from zero, indicating that they are both stationary. The coefficient of time T for IO_t is statistically significant, which is consistent with the fact that institutional ownership increases over time. I therefore use the time trend coefficient 0.001 to calculate the detrended IO series.

Panel B of Table 9 shows that the detrended IO is negatively correlated with the $alpha_t$ of the portfolio with top quintile P/S or P/E. When the abnormal return $alpha_t$ decreases (increases), stocks become more overvalued (undervalued) and the average institutional holdings also increase. These findings confirm that on average institutions ride stock overvaluation. In Panel C of Table 9, I use the significantly negative $alpha$ stock portfolio as the overvalued portfolio and the significantly positive $alpha$ stock portfolio as the undervalued portfolio. Column (1) shows that when the overvalued portfolio $alpha$

decreases, the detrended institutional investor holdings of the overvalued portfolio will increase. Column (2) shows that when the undervalued portfolio *alpha* increases, institutional investors do not significantly increase their weights on the undervalued portfolio. Panel C suggests that institutional investors ride stock overvaluation and that they do not significantly change their holdings respond to stock undervaluation.

6. Robustness tests

6.1. Adjust for overlapping *alpha* by Hansen–Hodrick standard errors

The main misvaluation measurement variable *alpha* is estimated by the six-factor model with rolling five-year windows. Because the rolling regressions are based on monthly stock return data, the *alpha* estimators suffer an overlapping problem. The overlapping of *alpha* estimations creates a moving average error term. Therefore coefficients estimated by OLS regressions would be inefficient and hypothesis tests would be biased (Hansen and Hodrick, 1980).

Following Hansen and Hodrick (1980), I estimate regression (3) by calculating the Hansen–Hodrick standard errors, and re-calculate the t-ratios for all the regression coefficients.[21] The Hansen–Hodrick standard error estimator is heteroskedasticity and autocovariance consistent (HAC) and provides asymptotically valid hypothesis tests for overlapping data. Because institutional ownership variables are at a quarterly frequency and *alpha* is estimated by a rolling five-year window, the alpha estimators are in fact overlapped by 19 quarters. Table 10 shows that the relationship between institutional ownership and stock *alpha* are still significantly negative for all five regressions after adjusting the standard errors for overlapping *alpha* estimation.

[21] All the coefficients remain the same as in the Panel A of Table 7. Only the standard errors of coefficients and the p-values may change when using Hansen–Hodrick standard errors.

6.2. Average institutional ownership and stock rolling five-year *alpha*

In regression (3), the independent variable $alpha_t$ is estimated by the six-factor model over a rolling five year window between $t-5$ year and t. *Alpha* should measure stock misvaluation over the five-year period before time t. Therefore, I replace the dependent variable IO by $IO_{Average}$, the average of 20 quarterly institutional ownership IO between year $t-5$ and year t. Table 11 shows that there is still a significantly negative relationship between $IO_{Average}$ and $alpha$ for all $alpha$ measures. The coefficient of the significant $alpha$ dummy is -0.053 and significant at the 1% level, suggesting that the five-year average institutional ownership is 10.6% higher in overvalued stocks than undervalued stocks controlling for other stock characteristics. The coefficient of the actual $alpha$ is -1.70 and significant at the 1% level, suggesting that the five-year average institutional ownership in misvalued stocks increases by 1.70% as the actual $alpha$ decreases by 1%.

$$IO_{Average_{i,t}} = \frac{\sum_{t-19}^{t} IO_{i,t}}{20} \tag{5}$$

6.3. Institution fund inflow

One alternative explanation of my results is that individual investors invest more in institutions that ride stock misvaluation than institutions that do not. For example, during the Dot-com bubble period individual investors invested more in institutions that put more weight on technology stocks. To rule out this alternative explanation, I divide my sample into "high-inflow" and "low-inflow" quarters. Following Gompers and Metrick (2001), I define the institution fund inflows as the quarterly change in the total value of aggregate institutional holdings without any price appreciation or depreciation effects:

$$Inflow_t = \frac{\sum_{i}^{N}(MV_{i,t-1} * \triangle IO_{i,t})}{\sum_{i}^{N} MV_{i,t-1}} \tag{6}$$

where N is total number of stocks at time $t-1$, $MV_{i,t-1}$ is stock i's market value at time $t-1$, and $\triangle IO_{i,t}$ is the change in institutional ownership in stock i from time $t-1$ to t. Using the $Inflow_t$ measure, I sort all quarters in my sample and define the top half as "high inflow" and the bottom half as "low inflow". Regression (3) is estimated for both subsamples by using the Fama and Macbeth (1973) method and the pooled regression. Table 12 shows that the absolute value of coefficients on stock misvaluation measures in high-inflow quarters is less than its absolute value in low-inflow quarters. These results suggest that the action of institutional investors riding stock misvaluation is not driven by individual investors.

6.4. Subperiod analysis

Brunnermeier and Nagel (2004) find that hedge funds rode stock overvaluation during the Dot-com bubble. In order to preclude the possibility that my results are mainly driven by institutions speculating on internet stocks during that period, I exclude the observations between 1997 and 2001 from my sample. Untabulated results show that both cross-sectional and time-series test results for the remaining sample are similar to what I report in this paper.

Another concern of my finding is that institutions' tendency to ride stock misvaluation may change over time. For example, the number of hedge funds and mutual funds increased significantly after the late 1990s. To address this concern, I separate my sample into two subperiods, 1980–1994 and 1995–2010, and repeat my multivariate regression analysis for each subperiod. Table 13 presents the results and indicates that institutional investors had a higher tendency to ride stock misvaluation during the 1995–2010 subperiod, when mutual funds and hedge funds were more popular in the U.S. stock market. But my key results remain qualitatively similar during the 1980–1994 subperiod. Neither the Dot-com bubble nor the composition change of institutions drive the findings of this study.

6.5. Industry-specific or firm-specific?

During my sample period, certain industries went through overvaluation for a sustained period, for example, the technology industry in the late 1990s and the real estate industry in the late 2000s. Following the Fama–French 49 industry definition, I assign each stock in my sample to a corresponding industry based on its four-digit SIC code every quarter. I then check the multivariate regression (3) of institutional ownership on stock *alpha*s within each industry. To include more observations in each industry, I choose $alpha_{dummy}$ as my key independent variable, which is equal to 1 if the actual *alpha* is positive and 0 otherwise. Table 14 shows that my findings that institutional investors hold more overvalued stocks than undervalued stocks cross-sectionally are not driven by only a few industries. Among the 49 Fama–French industries, the estimated coefficient for $alpha_{dummy}$ is significantly negative for 31 industries, insignificantly nagative for 15 industries, and insignificantly positive for the other 3 (Candy & Soda; Beer & Liquor; and Entertainment). One possible explanation of this insignificance is the lack of observations. The other possible reason is that most of the industries with insignificantly negative $alpha_dummy$ coefficients or insignificantly positive coefficients are traditional industries such as agricultural, defense, textiles, mining, etc. Stocks in these industries are relatively easy to be priced and have less uncertainty.

6.6. Are institutional investors better off by investing in negative *alpha* stocks?

This paper shows that institutional investors invest more in negative *alpha* stocks than positive *alpha* stocks. Investment companies and independent investment advisors also have a higher tendency to do so than the other institution types. The implication of these results is that institutional investors ride stock misvaluation instead of trade against the misvaluation immediately. The next question is whether the trend chasing strategies of institutional investors are rational or not. That is, will the subsequent performance of the institutional investors be better off when institutional investors overweigh negative *alpha* stocks in their portfolios?

The ideal answer is to track individual institutional investors' time-series performance. However, this method is not feasible in my data sample. Institutional investor stock holdings are collected from the CDA/Spectrum S34 database that covers the entire range of institutional investors in the U.S. stock market. Banks, insurance companies, parents of mutual funds, pension funds, university endowments, and professional investment advisors (hedge funds) are all included. The advantage of this database is its comprehensiveness. The findings in this paper can represent the trading strategies of the average institutional investors in the U.S. stock market, not just a portion of institutional investors. However both fund number (FUNDNO) and manager number (MGRNO) identifiers in the CDA/Spectrum S34 database are re-used. According to the User's Guide to Thomson Reuters Mutual Fund and Investment Company Common Stock Holdings Databases on WRDS, FUNDNO and MGRNO do not provide a unique and permanent identifier for every fund or manager. The same FUNDNO or MGRNO usually represents a different and unrelated fund or manger if there is more than a one-year gap in the report date of stock holdings. For these reasons, the CDA/Spectrum S34 database has been rarely used in the previous literature studying institutional investor performance over time.

One alternative method is to investigate the relationship between institutional ownership and stock forward looking *alpha*. I calculate the individual stock six-factor model $alpha_t$ from time t to $t+5$ years and the individual stock six-factor model $alpha_t$ from time t to $t+3$ years. Then I check the relationship between institutional ownership at time t and the five-year (three-year) forward looking *alpha*s. Both the Fama and Macbeth (1973) method and the pooled regression method are applied to estimate regression (3). Table 15 shows that institutional ownership and the stock forward *alpha* is positively correlated. This positive relationship is significant when the forward three-year *alpha* is used, but insignificant when the forward five-year *alpha* is used. If I divide institutional investors into three types following Kamara et al. (2008), then the coefficients of forward *alpha* is larger for investment companies and independent investment companies than for the other two types. All these results provide weak evidence that institutional investors riding stock misvaluation may generate a positive *alpha* in the future. Institutional investors are rational trend chasers on average.

The other alternative method is to sort stocks into portfolios by their last quarter institutional ownership and stock *alpha*, then the portfolio returns may indicate whether institutional investors can make a profit by investing in negative *alpha* stocks. However, the high institutional holdings portfolio tends to include more large company stocks because institutional investors prefer to invest in firms of larger size (Gompers and Metrick, 2001). In addition, institutional ownership has increased over my sample period. Therefore, I control for both time and firm size in forming portfolios. I follow Field and Lowry (2009) and employ the fractional logit methodology. Each quarter, I model the conditional mean of institutional ownership percentage as a logistic function:

$$\mathbb{E}(IO_{i,t} \mid x) = \frac{exp\{\beta_1 + \beta_2 * Size_{i,t}\}}{1 + exp\{\beta_1 + \beta_2 * Size_{i,t}\}} \tag{7}$$

where $IO_{i,t}$ is the institutional ownership for firm i at quarter t; $Size_{i,t}$ is firm i's log total assets at quarter t. The parameters are estimated for each quarter. This method accounts for the fact that institutional ownership has values between zero and one by definition. The difference between actual institutional ownership and expected institutional ownership for each firm is calculated as the unexpected institutional ownership.

I next assign a stock in a portfolio at each quarter if the stock's unexpected institutional ownership is among the top 20% in the previous quarter and the stock's *alpha* estimated by the six-factor model over five-year windows is negative. Panel A of Table 16 shows the descriptive statistics for the portfolio quarterly returns and the number of stocks in the portfolio. The average quarterly raw portfolio returns is 4.2% if the *alpha* dummy is used when forming the portfolio and 5.1% if the significant *alpha* dummy is used when forming the portfolio. Panel B of Table 16 shows the regression results of the portfolio quarterly returns based on the Fama–French three-factor model. To account for the stock number changes in the portfolio, regressions are estimated by WLS regressions, in which each quarterly return is weighted by the number of stocks in the portfolio. The intercept in the regression measures any abnormal performance of the portfolio. The results show that both portfolios have significantly positive abnormal returns. Overall, Table 16 indicates that institutional investors do make a positive profit by riding stock misvaluation.

7. Conclusion

This paper investigates whether institutional investors ride or trade against stock misvaluation. Using all the stocks covered by the CRSP between 1980 and 2010, I identify mispriced stocks by three general asset pricing models and study the institutional holdings of these mispriced stocks. Cross-sectionally, the aggregate institutional investor overweighs (underweighs) the overvalued (undervalued) stocks in its portfolio. The time-series relationship between institutional holdings and the degree of stock overvaluation is also significantly positive. Institutional investors dominate the U.S. stock market in terms of both market share and trading volume. When stock misvaluation is still observed in such an institutionalized market, the role of institutions as arbitrageurs is compromised.

Several extensions of this paper could be pursued in the future. Firstly, it is interesting to study the relationship between fund mangers' pay-performance contacts and their holdings of mispriced stocks. Secondly, it is also interesting to investigate whether the fund governance has any effect on the fund's holdings of mispriced stocks. Thirdly, the synchronization among the largest institutions and its effect on stock misvaluation can be studied so that we can answer the question whether synchronization risk really delays arbitrage. And lastly, if a panel data sample covers both institutional investor holdings and their performance, then we may directly test the hypothesis that institutional investors are better off to ride stock misvaluation.

Appendix

Appendix A.1

This appendix describes my data sources and sample selection process.

Thomson CDA/Spectrum S34 Institutional Investor Ownership Data. The backbone of my empirical tests is institutional investor stock holding data from Thomson Reuters (also known as CDA/Spectrum S34). According to the 1978 amendment to the Securities and Exchange Act 1934, all institutional investors with greater than $100 million of securities under discretionary management must report their holdings to the Securities and Exchange Commission (SEC) in their 13F report. Thomson Reuters collects institutional investor holding information from 13F filings to the SEC at each quarter end. There are some exclusions in 13F filings: (1) Small holdings under 10,000 shares or $200,000; (2) Holdings that are confidential for some particular reasons; (3) Holdings that could not be matched with a master security file. I focus on the institutional investor report dates found in the Thomson Reuters 13F dataset, and adjust the holding information if an institutional investor's file date is later than its report date.[22] The 13F data sample period is from 1980 to 2010.

All institutions in the CDA/Spectrum S34 database are classified into five types: (1) Bank, (2) Insurance company, (3) Investment Company (Mutual Fund), (4) Independent Investment Advisor and (5) Others (e.g., Pension Fund, University Endowment, and Foundation). The institution type information is not accurate after 1998. Therefore my studies related to institutional investor types are restricted to the time period from 1980 to 1997.

CRSP Stock Price and Return Data. Stock prices, returns, and trading volume at month end, and daily end are obtained from the CRSP/COMPUSTAT Merged Database, which includes all U.S. ordinary common stocks (i.e., CRSP share code 10 or 11) listed on NYSE, AMEX, and NASDAQ. ADRs, REITS, closed end funds, and foreign incorporated companies are excluded from my sample. I also collect stock dividend returns, shares outstanding, trading volume, and firm market value from the CRSP/COMPUSTAT Merged Database. To avoid any potential confounding effect of recent IPOs, only firms that have been recorded on the CRSP for at least 12 months are included in my sample. To alleviate the effect of bid–ask bounces on the empirical studies, I exclude stocks with prices below $3 at the end of each month. To account for market maker activity in calculating NASDAQ trading volume, I divide NASDAQ firms' trading volume by two in the main analysis (Atkins and Dyl, 1997).[23] My CRSP sample period is from 1980 to 2011.

[22] The only reason to be concerned about the file date is that when the file date is later than the report date and when stock splits occur between an institutional investor's report date and file date. I recover the correct number of holding shares as of the report date by using the CRSP share adjustment factors.

[23] NASDAQ overstating trading volume may no longer exist after 1997, because the SEC changed its order-handling rules and trade-reporting rules after that date. In 2010, the SEC reported that by the mid-2000s, more than 40 percent of NASDAQ transactions were being handled by Electronic Communication Networks (ECNs). Since ECNs rarely double count their trades, reported volumes may not go up if some ECN trading does not come from dealers. Anderson and Dyl (2005) find that NASDAQ volumes are still biased (37%) in comparison to NYSE reported volumes for their sample period from 1997 to 2002, but not by as much as they had been (50%). As a robustness check, I take NASDAQ firm's trading volume as it is and redo the analysis. This alternative specification does not significantly change my original findings.

Corporate Accounting Data and Short Interest Data from COMPUSTAT. Corporate accounting data, such as book equity, earnings, and cash flows, come from COMPUSTAT. Short interest data for stocks listed on NYSE and NASDAQ, and S&P 500 index constitutes are also collected from the COMPUSTAT monthly file. The sample period for COMPUSTAT data is from 1980 to 2011.

Analysts' Earnings Forecasts from I/B/E/S. Financial analysts' earnings forecasts are retrieved from the I/B/E/S Unadjusted Summary File.[24] The Unadjusted Summary File contains summary statistics on analyst earnings per share (EPS) forecasts. Mean, median and standard deviation of analyst earnings forecasts are included. I/B/E/S data manual indicates that these data are all calculated on the third Thursday of each month based on the individual records from the Unadjusted Detail History File. The sample period is from 1980 to 2011.

Six-Factor Time-Series Data from the WRDS. From the WRDS, I collect monthly time series data for excess return on the market portfolio $R_{m,t} - R_{f,t}$, the difference between the average return on the three small firm portfolios and average return on the three big firm portfolios SMB_t, the difference between the average return on two high book-to-market (value) stock portfolios and the average return on the two low book-to-market (growth) stock portfolios HML_t, and the difference between the average return on two high prior return portfolios and the average return on two low prior return portfolios UMD_t. These three factors are proposed by Fama and French (1993). The fourth factor momentum is proposed by Carhart (1997). And the fifth factor which I collect from the WRDS is Pastor–Stambaugh VW liquidity factor (Pastor and Stambaugh, 2003) with monthly frequency. The sample period is from 1980 to 2010.

Fama–French 49 Industries from Kenneth R. French's Website. Based on stocks' SIC codes, Fama and French assign each NYSE, AMEX, and NASDAQ stock to an industry portfolio at the end of June. I use their 49 industry classification in my study. The data is downloaded from Kenneth R. French's website.

Appendix A.2

This appendix describes the definitions of variables used in my empirical tests.

Appendix A.2.1

This appendix describes how valuation ratios are constructed in this paper. The #s in parentheses refer to data items from the COMPUSTAT quarterly file.

P: Share price from CRSP, at the end of each month.

[24] I/B/E/S also provides an Adjusted Summary File, which adjusts EPS for stock splits and stock dividends since the date of forecasts to today. Although this adjustment makes today's EPS comparable with its historical values, it causes two issues. First, the rounding issue after the adjustment makes some of the standard deviation and the mean of analysts' EPS forecasts equal to zero. The adjustment distorts the rank of the historical EPS. For example: firm A and B's historical EPS are $1 and $1.49, respectively. If both firms carry out a one-to-ten stock split after the historical EPS report date, then I/B/E/S adjusts both firms' EPS to be ten cents.

S: Per share sales = sum of four consecutive quarterly sales (#12 saleq) deflated by shares outstanding (#25 cshoq).

E: 12-month moving earnings per share (#58 epsx12) excluding extraordinary items.

Appendix A.2.2

This appendix describes how the proxy variables for dispersion of investor opinions and short sale constraints are constructed:

$$\text{SD(EPS)} = \frac{\text{SD of EPS Estimation}}{\text{ABS(Mean of EPS Estimation)}} \tag{8}$$

SD(EPS): normalized standard deviation of analyst's EPS estimation. Data are collected from the I/B/E/S Unadjusted Summary File. Diether et al. (2002) and Boehmer et al. (2006) use this measure to capture dispersion of investor opinion.
SIGMA: the unsystematic risk term of stock returns. Following the Brown and Warner (1985) market model, I run a CAPM regression over a rolling three-month window by using daily stock excess returns and market excess returns. The standard deviations of the regression error terms are recorded at the end of each month. For a robustness check, I also use a rolling six-month window and get similar results. Harrison and Raviv (1993) and Shalen (1993) find that the return volatility is positively related to dispersion of I/B/E/S analysts' EPS forecasts, and Boehmer et al. (2006) use $SIGMA$ as one of their dispersion of investor opinion proxies.

$$\text{Turnover} = \frac{\text{Trading Volume}}{\text{Total Share Outstandings}} \tag{9}$$

Turnover: past one-month, three-month, six-month, and twelve-month trading volume. Due to space availability, I only report results by using past three-month trading volume. But my results are qualitatively similar by using other trading volume periods. Diether et al. (2002), Boehmer et al. (2006) and Cao and Ou-Yang (2009) use this measure to capture dispersion of investor opinion. Following the previous literature, the NASDAQ trading volume is divided by two to account for market maker activity in calculating the NASDAQ trading volume.[25]

$$\text{SI} = \frac{\text{Number of Shares Shorted}}{\text{Total Shares Outstanding}} \tag{10}$$

SI: short interest. Figlewski (1981) finds that the unobserved demand to short a stock rises with the observed short interest level and firms with high observed short interests are more difficult to be shorted. Ofek and Richardson (2003) also find that short interest was considerably higher for Internet stocks than for "old economy" firms during the period of January 1998 to December 2000.

[25] See Atkins and Dyl (1997) for a detailed discussion of this practice.

Appendix A.2.3

This appendix describes how control variables for stock characteristics are constructed by following Gompers and Metrick (2001) with minor modifications.

Size: market capitalization at the end of quarter t.

B/M: most recent book value before quarter t, divided by Size at the end of quarter t.

Yield: dividend yield for the past 12 months before the end of quarter t.

Price: stock price per share at the end of quarter t

Volatility: the variance of monthly stock returns over the past 24 months before the end of quarter t.

Momentum1**:** past three-month gross return before the end of quarter t.

Momentum2**:** past nine-month gross return preceding the beginning of Momentum1 measurement period.

Turnover: trading volume at the end of quarter $t - 1$ divided by shares outstanding.

S&P 500: dummy variable which is equal to 1 if a stock is in S&P 500 index, and 0 otherwise.

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Figure 1: The rise of institutions in the U.S. stock market

This figure shows the growth of institutional ownership in the U.S. stock market. Figure 1.1 presents the cumulative institutional holdings as a percentage of total stock market value for all institutions, top 100, top 10, and the largest institution ranked by market value of institutional holdings. Figure 1.2 plots institutional holdings as a percentage of total stock market value by five institution types: Banks, Insurance Companies, Mutual Funds, Investment Advisors, and Others. Figure 1.3 plots the number of total institutions and the number of institutions by five types. All numbers are calculated at the end of each year. The sample period is from 1980 to 2010. In Figure 1.2 and Figure 1.3, plots related to institution types only span from 1980 to 1997.

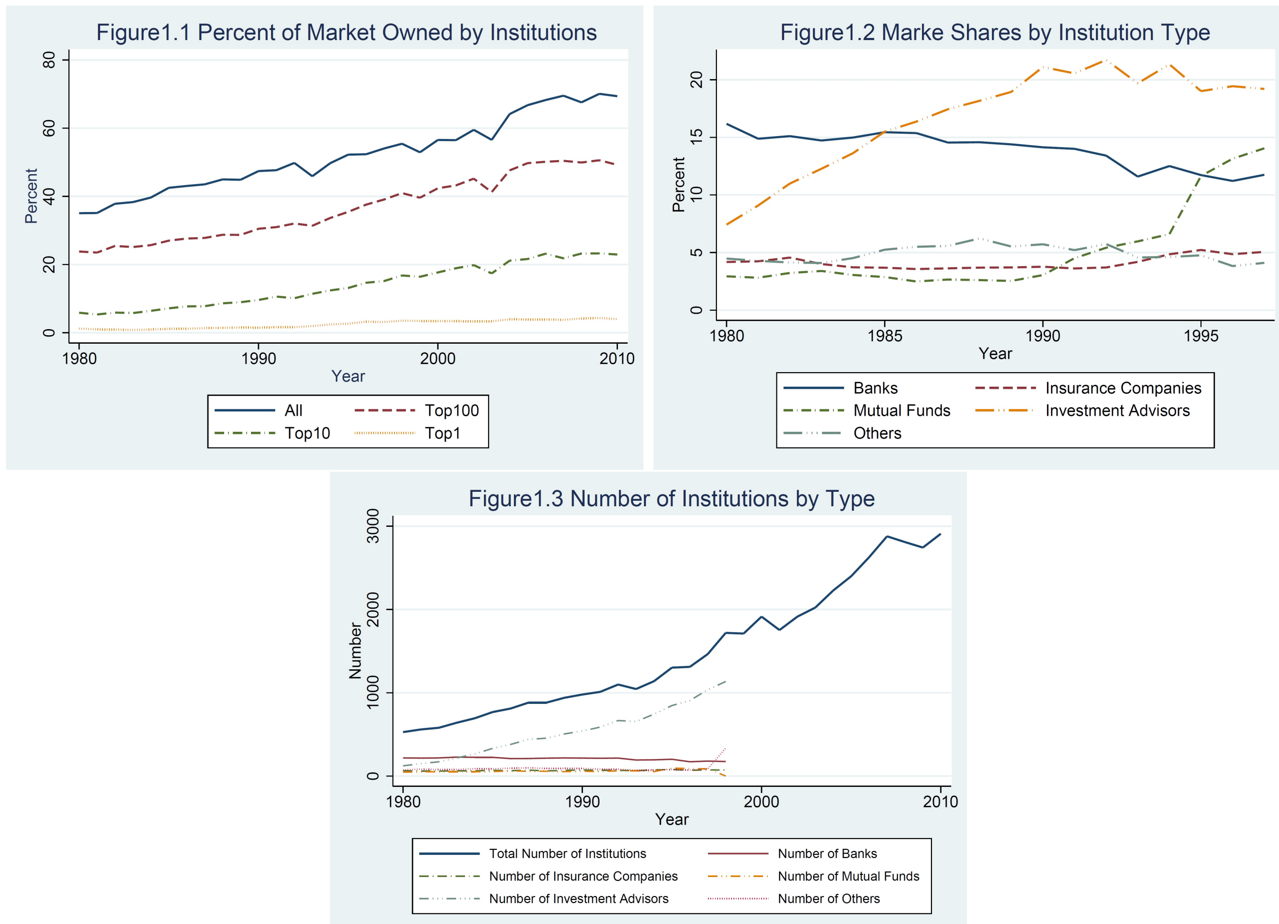

Figure 2: Nonzero *alpha* stock in the institutional investor portfolio versus in the market portfolio

Figure 2.1. Significantly negative *alpha* stocks. The top panel of Figure 2.1 presents the time series weights of significantly negative alpha (overvalued) stocks in the institutional investor portfolio and the weights of significantly negative alpha (overvalued) stocks in the market portfolio. The bottom panel of Figure 2.1 presents the time series differences between the overvalued stock weights in the institutional investor portfolio and the overvalued stock weights in the market portfolio. Overvalued stocks have significantly (10%) negative *alpha*s estimated by the six-factor model with rolling five-year windows: $R_{p,t} - R_{f,t} = \alpha_p + \beta_p(R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + u_p UMD_t + l_p L_t + b_p BAB_t + \epsilon_{p,t}$; where $R_{m,t} - R_{f,t}$, SMB_t, and HML_t are the Fama and French (1993) three factors; UMD_t is the Carhart (1997) momentum factor; L_t is the Pastor and Stambaugh (2003) liquidity factor; and BAB_t is the Frazzini and Pedersen (2014) betting against beta factor.

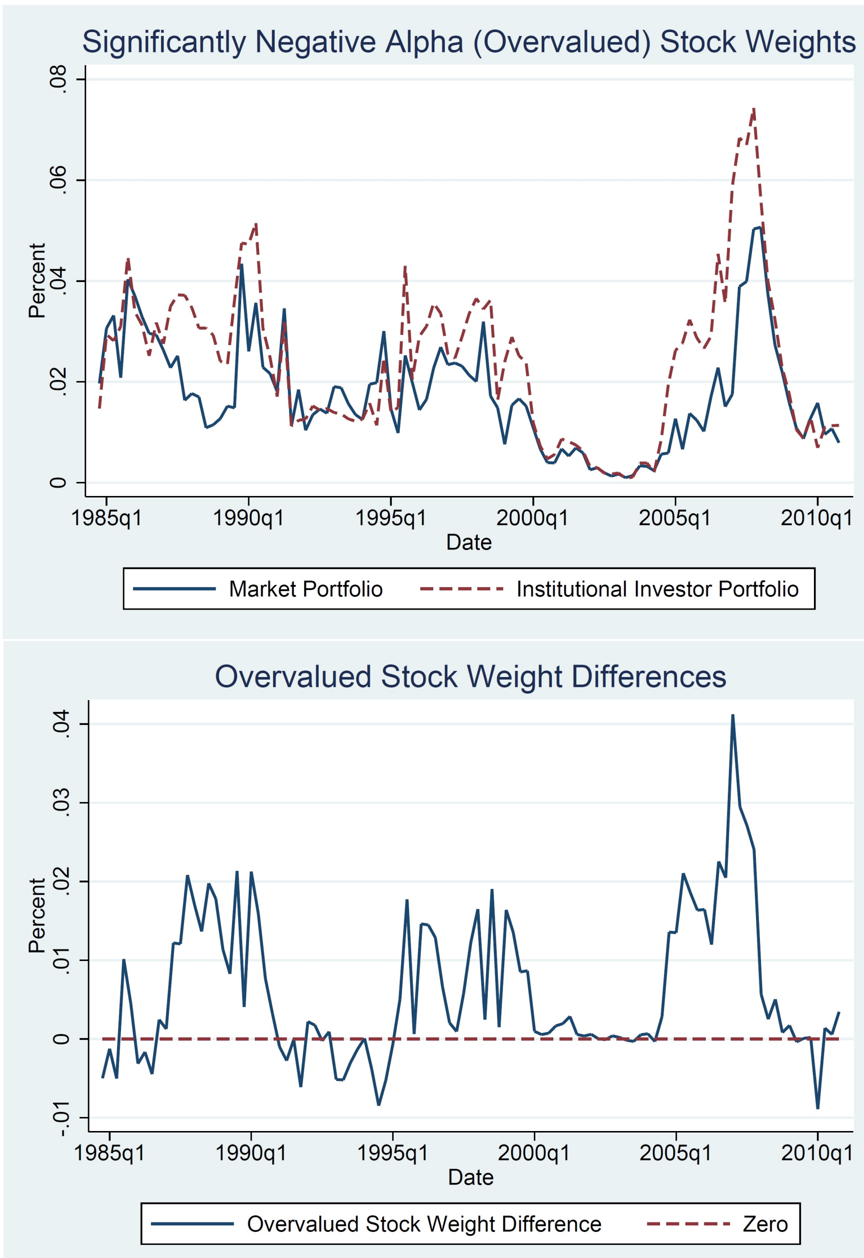

Figure 2.2. Significantly positive *alpha* stocks. The top panel of Figure 2.2 presents the time series weights of significantly positive alpha (undervalued) stocks in the institutional investor portfolio and the weights of significantly positive alpha (undervalued) stocks in the market portfolio. The bottom panel of Figure 2.2 presents the time series differences between the undervalued stock weights in the institutional investor portfolio and the undervalued stock weights in the market portfolio. Undervalued stocks have significantly (10%) positive *alpha*s estimated by the six-factor model with rolling five-year windows: $R_{p,t} - R_{f,t} = \alpha_p + \beta_p(R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + u_p UMD_t + l_p L_t + b_p BAB_t + \epsilon_{p,t}$; where $R_{m,t} - R_{f,t}$, SMB_t, and HML_t are the Fama and French (1993) three factors; UMD_t is the Carhart (1997) momentum factor; L_t is the Pastor and Stambaugh (2003) liquidity factor; and BAB_t is the Frazzini and Pedersen (2014) betting against beta factor.

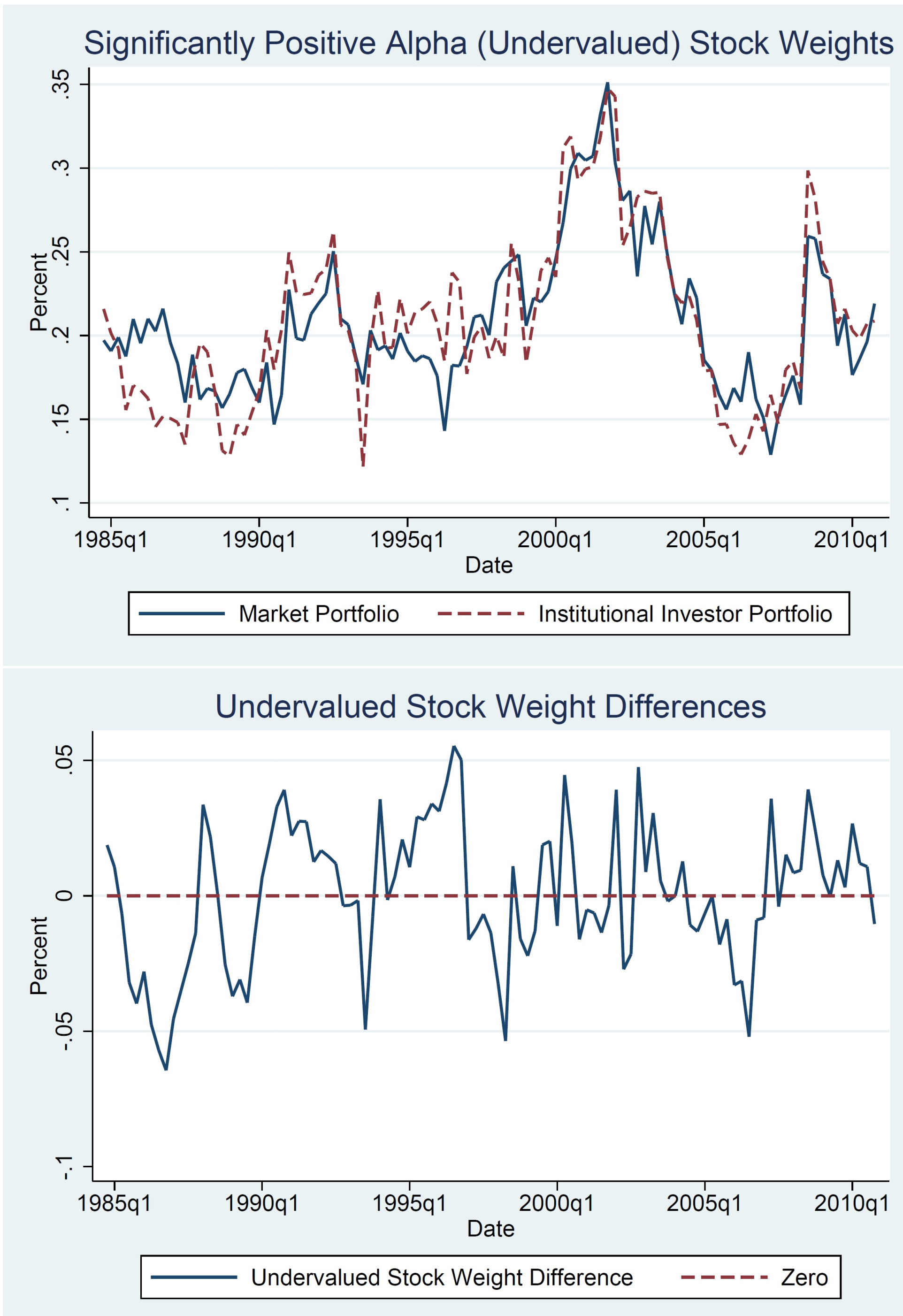

Figure 3: Weights of top and bottom valuation ratio decile portfolios in the institutional investor portfolio versus in the market portfolio

Figure 3.1. P/S. At the end of each quarter, I sort stocks into ten decile portfolios by P/S. The ratios of the market value of top (D10) and bottom decile (D1) portfolios to the market portfolio value are calculated at quarterly end as benchmarks. The ratios of the market value of top and bottom decile portfolios held by institutions to the market value of aggregate institutional investors' portfolio are also calculated at quarterly end. The sample period is from March 1980 to December 2010.

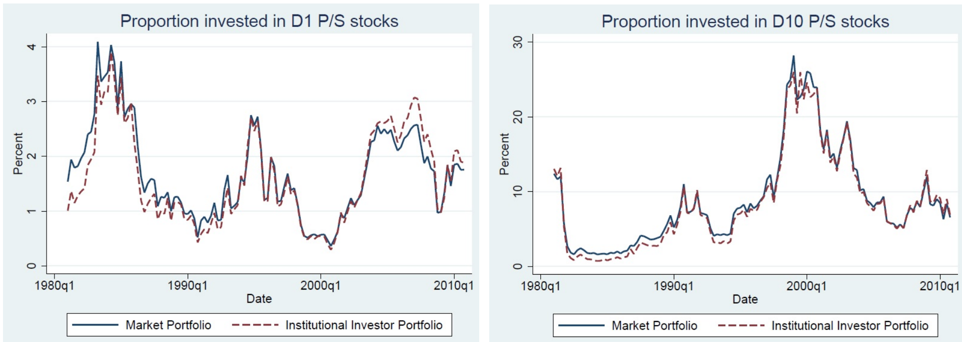

Figure 3.2. P/E (Positive only). At the end of each quarter, I sort stocks into ten decile portfolios by P/E. Negative P/E stocks are excluded. The rest is similar to Figure 3.1

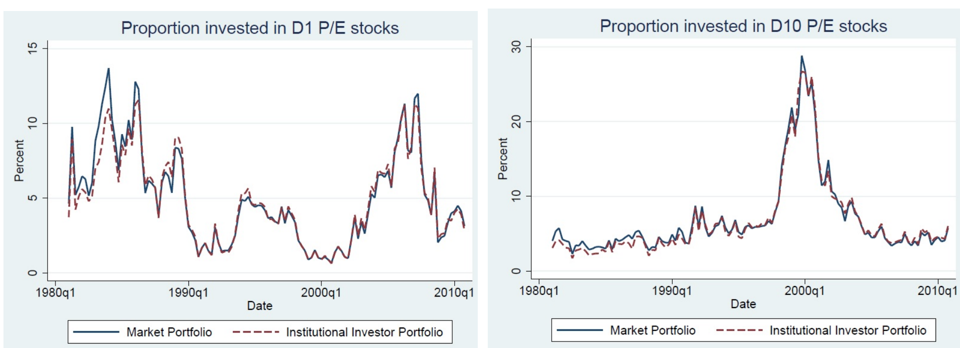

Figure 3.3. Negative P/E**.** At the end of each quarter, I sort all negative P/E stocks into one portfolio. The ratio of the market value of negative P/E stocks to the market portfolio value are calculated at quarterly end as benchmarks. The ratio of the market value of negative P/E stock portfolio held by institutions to the market value of aggregate institutional investors' portfolio are also calculated at quarterly end. The sample period is from March 1980 to December 2010.

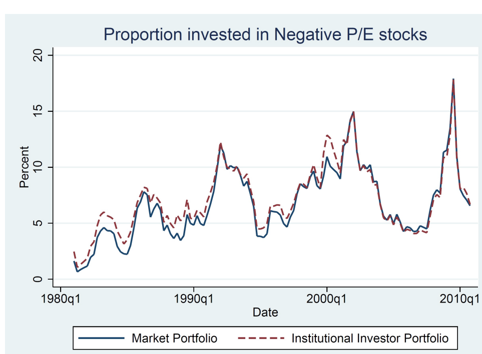

Table 1: Summary statistics

Panel A. Time series of institutional holdings. This panel presents the number of reported institutional positions, the number of stocks on the market, the number of institutional investors, the total market value of institutional holdings (billion dollars), the stock market value (billion dollars), and the percentage of stock market share held by institutions. The sample period is from 1980 to 2010.

Year	**Reported Positions**	**Number of Stocks**	**Institution Number**	**Market Value of Holdings**	**Total Stock Market Value**	**Percentage**
Dec-80	90,783	4,698	528	460.91	1,314.65	35.06%
Dec-85	158,129	5,724	769	886.83	2,086.00	42.51%
Dec-90	206,216	5,705	979	1,303.72	2,749.60	47.41%
Dec-95	324,175	6,952	1,302	3,299.82	6,317.43	52.23%
Dec-00	445,079	6,340	1,907	8,094.32	14,316.06	56.54%
Dec-05	510,220	4,758	2,399	9,874.37	14,795.22	66.74%
Dec-10	521,529	3,952	2,908	10,057.83	14,497.44	69.38%

Panel B. Descriptive statistics. This panel presents the descriptive statistics of institutional investors and their holdings. In the first two rows, the number of institutional investors and the number of stocks in the stock market are calculated at the end of each quarter, and the descriptive statistics of these two time-series data are reported. In the last two rows, I calculate the cross-sectional average of the number of stocks in institutional investors' portfolios and the cross-sectional average of the total value of their portfolio across institutions at the end of each quarter, respectively. Then the descriptive statistics of time-series of cross-sectional averages are reported. The value of institutional holdings is in billion dollars. The sample period is from 1980 to 2010.

	Average	**Median**	**S.D.**	**Min.**	**25th**	**75th**	**Max.**
Number of institutions	1,436	1,203	740	466	839	1,922	2,907
Number of stocks	4,604	4,389	820	2,878	6,477	4,106	5,020
Number of stocks in institutions portfolios	219	221	27	161	194	240	269
Value of institutional holdings (billions)	2.54	0.32	1.34	0.66	0.75	2.27	5.23

Panel C. The number of institutional investors per stock. This panel presents the summary statistics for the number of institutional investors holding one stock at each year end. All stocks in the summary statistics have at least one institutional owner. The sample period is from 1980 to 2010.

Date	Mean	Median	S.D.	Max.
1980/12	26.74	6	52.67	472
1981/12	26.5	6	52.39	497
1982/12	27.29	7	52.65	513
1983/12	27.36	8	52.85	551
1984/12	28.23	8	55.49	592
1985/12	32.23	10	60.91	634
1986/12	32.55	10	61.15	632
1987/12	34.28	11	66.02	687
1988/12	36.62	12	68.74	694
1989/12	39.17	13	73.27	689
1990/12	40.08	14	74.94	736
1991/12	42.29	15	76.2	716
1992/12	46.52	17	81.94	766
1993/12	41.61	16	72.04	728
1994/12	43.98	17	76.62	777
1995/12	49.2	19	85.27	881
1996/12	47.29	18	83.71	902
1997/12	52.86	20	92.1	985
1998/12	59.75	21	106.24	1,100
1999/12	72.62	32	117.76	1,133
2000/12	82.12	35	130.33	1,231
2001/12	86.22	45	126.12	1,156
2002/12	96.33	53	134.6	1,256
2003/12	113.41	74	144.32	1,347
2004/12	124.42	83	151.51	1,366
2005/12	125.27	80	157.9	1,409
2006/12	134.7	88	165.62	1,519
2007/12	138.67	87	176.1	1,608
2008/12	133.24	84	170.03	1,557
2009/12	147.55	97	182.86	1,618
2010/12	156.38	99	194.61	1,689

Table 2: Summary statistics of individual stock *alphas*

Panel A. Six-factor model *alpha* with five-year rolling windows. Individual stock monthly returns are fitted to the six-factor model with a five-year rolling window at the end of each month: $R_{p,t} - R_{f,t} = \alpha_p + \beta_p(R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + u_p UMD_t + l_p L_t + b_p BAB_t + \epsilon_{p,t}$; where $R_{m,t} - R_{f,t}$, SMB_t, and HML_t are the Fama and French (1993) three factors; UMD_t is the Carhart (1997) momentum factor; L_t is the Pastor and Stambaugh (2003) liquidity factor; and BAB_t is the Frazzini and Pedersen (2014) betting against beta factor. *Alphas* are estimated from December 1984 to December 2010. The summary statistics of the number of negative *alphas*, positive *alphas*, significantly negative *alphas* (20%, two-tailed), insignificant *alphas*, and significantly positive *alphas* (20%, two-tailed) are reported.

	Negative	**Positive**	**Negative at 10%**	**Insignificant**	**Positive at 10%**
Maximum	2,811	2,025	445	3,390	755
Minimum	1,594	1,023	62	2,318	247
Average	2,099	1,582	256	2,992	433
25 Percentile	1,745	1,418	180	2,728	366
75 Percentile	2,430	1,789	331	3,256	487
S.D.	357	241	94	285	99

Panel B. Six-factor model *alpha* with three-year rolling windows. Individual stock monthly returns are fitted to the six-factor model with a three-year rolling window at the end of each month: $R_{p,t} - R_{f,t} = \alpha_p + \beta_p(R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + u_p UMD_t + l_p L_t + b_p BAB_t + \epsilon_{p,t}$; where $R_{m,t} - R_{f,t}$, SMB_t, and HML_t are the Fama and French (1993) three factors; UMD_t is the Carhart (1997) momentum factor; L_t is the Pastor and Stambaugh (2003) liquidity factor; and BAB_t is the Frazzini and Pedersen (2014) betting against beta factor. *Alphas* are estimated from December 1982 to December 2010. The summary statistics of the number of negative *alphas*, positive *alphas*, significantly negative *alphas* (20%, two-tailed), insignificant *alphas*, and significantly positive *alphas* (20%, two-tailed) are reported.

	Negative	**Positive**	**Negative at 10%**	**Insignificant**	**Positive at 10%**
Maximum	3,105	2,707	657	4,320	832
Minimum	1,747	1,433	138	2,839	258
Average	2,328	2,047	377	3,538	461
25 Percentile	1,993	1,825	281	3,222	376
75 Percentile	2,589	2,242	458	3,798	521
S.D.	374	327	119	392	112

Table 3: Valuation ratios and portfolio *alphas*

Panel A. Top and bottom quintile portfolios. Each month, all stocks are sorted into five quintile portfolios based on their valuation ratios at the end of the previous month. Stocks in the Quintile 5 portfolios have the highest valuation ratios. Two valuation ratios are used: P/S and P/E. I adjust negative P/E by two methods. Firstly, I exclude negative P/E stocks from the sample. Secondly I sort stocks by the negative earnings yield (E/P). Portfolios are rebalanced monthly. Equally-weighted (EW) and value-weighted (VW) monthly portfolio returns are calculated. Portfolios' abnormal returns α_p are estimated by the six-factor model: $R_{p,t} - R_{f,t} = \alpha_p + \beta_p(R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + u_p UMD_t + l_p L_t + b_p BAB_t + \epsilon_{p,t}$; where $R_{m,t} - R_{f,t}$, SMB_t, and HML_t are the Fama and French (1993) three factors; UMD_t is the Carhart (1997) momentum factor; L_t is the Pastor and Stambaugh (2003) liquidity factor; and BAB_t is the Frazzini and Pedersen (2014) betting against beta factor. Portfolio abnormal returns α_p are presented as percentages per month. The sample period is from January 1980 to December 2010. p-values are reported in parentheses. $*$,$**$,$***$ denote significance levels of 10%, 5%, and 1%, respectively, two-tailed.

		P/S		P/E	
		EW	**VW**	**EW**	**VW**
All Observations	Quintile 5	-0.5***	-0.1**	-0.5***	-0.3***
		(0.000)	(0.021)	(0.000)	(0.000)
	Quintile 1	1.0***	0.2*	-0.7***	-0.5***
		(0.000)	(0.080)	(0.000)	(0.001)
P/E (Positive Only)	Quintile 5			-0.5***	-0.3***
				(0.000)	(0.001)
	Quintile 1			1.5***	0.6***
				(0.000)	(0.000)
−E/P	Quintile 5			-0.2*	-0.6***
				(0.082)	(0.001)
	Quintile 1			1.2***	0.4***
				(0.000)	(0.000)

Panel B. Decile portfolios sorted by valuation ratios. Each month, all stocks are sorted into ten decile portfolios based on their valuation ratios at the previous month end. Stocks in the Decile 10 portfolios have the highest valuation ratios. Two valuation ratios are used: P/S, P/E. I adjust negative P/E by two methods. Firstly, I exclude negative P/E stocks from the sample. Secondly I sort stocks by the negative earnings yield (E/Y). Portfolios are rebalanced monthly. Equally-weighted (EW) and value-weighted (VW) monthly portfolio returns are calculated. Portfolio abnormal returns α_p are estimated by the six-factor model: $R_{p,t} - R_{f,t} = \alpha_p + \beta_p(R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + u_p UMD_t + l_p L_t + b_p BAB_t + \epsilon_{p,t}$; where $R_{m,t} - R_{f,t}$, SMB_t, and HML_t are the Fama and French (1993) three factors; UMD_t is the Carhart (1997) momentum factor; L_t is the Pastor and Stambaugh (2003) liquidity factor; and BAB_t is the Frazzini and Pedersen (2014) betting against beta factor. Portfolio abnormal returns α_p are presented as percentages per month. The sample period is from January 1980 to December 2010. p-values are reported in parentheses. $*$,$**$,$***$ denote significance levels of 10%, 5%, and 1%, respectively, two-tailed.

	P/S		**P/E (Positive Only)**		**−E/P**	
	EW	**VW**	**EW**	**VW**	**EW**	**VW**
Decile 1	1.4***	0.4**	1.8***	0.7***	1.6***	0.6***
	(0.000)	(0.026)	(0.000)	(0.000)	(0.000)	(0.000)
Decile 2	0.7***	0.2*	1.1***	0.6***	0.8***	0.4***
	(0.000)	(0.092)	(0.000)	(0.000)	(0.000)	(0.000)
Decile 3	0.4***	-0.0	0.7***	0.3***	0.3***	0.2*
	(0.000)	(0.867)	(0.000)	(0.010)	(0.000)	(0.082)
Decile 4	0.3***	0.0	0.4***	0.2	-0.0	-0.0
	(0.001)	(0.592)	(0.000)	(0.131)	(0.956)	(0.993)
Decile 5	0.2**	0.0	0.1	0.1	-0.2**	-0.1
	(0.014)	(0.743)	(0.257)	(0.255)	(0.038)	(0.265)
Decile 6	0.1	-0.0	-0.0	-0.1	-0.3***	-0.2**
	(0.243)	(0.934)	(0.625)	(0.601)	(0.000)	(0.014)
Decile 7	-0.1	0.0	-0.1*	-0.1	-0.4***	-0.2
	(0.380)	(0.627)	(0.073)	(0.131)	(0.000)	(0.194)
Decile 8	-0.2**	-0.0	-0.3***	-0.2**	-0.7***	-0.6***
	(0.030)	(0.643)	(0.001)	(0.027)	(0.000)	(0.000)
Decile 9	-0.3***	-0.1	-0.5***	-0.4***	-0.5**	-0.7***
	(0.002)	(0.252)	(0.000)	(0.001)	(0.026)	(0.000)
Decile 10	-0.7***	-0.2*	-0.6***	-0.3**	-0.01**	-0.6**
	(0.000)	(0.082)	(0.000)	(0.032)	(0.011)	(0.027)

Table 4: Misvaluation by dispersion of opinions and short sale constraints

Each month, stocks are sorted into five quintile portfolios based on the dispersion of opinions proxy at the end of the previous month. Then each quintile portfolio is further divided into five groups based on the proxy variable for short sale constraints at the end of the previous month. Following Boehmer et al. (2006), the dispersion proxy is estimated by the vicile-based model in Panel A, and is estimated by continuous-value model in Panel B. "Vicile" is used in Boehmer et al. (2006), and it means "twenty times". The word is based from Latin *vicie*. The equally-weighted (EW) and valued-weighted (VW) monthly returns of portfolios with the highest dispersion of opinions and short sale constraints (Q5 & Q5) and of portfolios with the lowest dispersion of opinions and short sale constraints (Q1 & Q1) are calculated. Portfolio abnormal returns α_p are estimated by the six-factor model: $R_{p,t} - R_{f,t} = \alpha_p + \beta_p(R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + u_p UMD_t + l_p L_t + b_p BAB_t + \epsilon_{p,t}$; where $R_{m,t} - R_{f,t}$, SMB_t, and HML_t are the Fama and French (1993) three factors; UMD_t is the Carhart (1997) momentum factor; L_t is the Pastor and Stambaugh (2003) liquidity factor; and BAB_t is the Frazzini and Pedersen (2014) betting against beta factor. Portfolio abnormal returns α_p are presented as percentages per month. Both Ordinary Least Squares (OLS) and Weighted Least Squares (WLS) regressions are used. The weights in WLS are the number of stocks in portfolios each month. p-values are reported in parentheses. $*$,$**$,$***$ denote significance levels of 10%, 5%, and 1%, respectively, two-tailed.

Panel A. Six-factor model *alpha* with constraint and dispersion estimated by the vicile-based model

	EW		**VW**	
	OLS	**WLS**	**OLS**	**WLS**
Q5&Q5	-0.9**	-0.7***	-1.3***	-1.1***
	(0.031)	(0.002)	(0.009)	(0.003)
Q1&Q1	0.1*	0.1*	0.1	0.1
	(0.086)	(0.088)	(0.252)	(0.287)

Panel B. Six-factor model *alpha* with constraint and dispersion estimated by continuous-value model

	EW		**VW**	
	OLS	**WLS**	**OLS**	**WLS**
Q5&Q5	-0.9**	-0.6***	-1.5***	-1.1***
	(0.051)	(0.009)	(0.004)	(0.011)
Q1&Q1	0.1*	0.1*	0.1	0.1
	(0.086)	(0.088)	(0.267)	(0.312)

Table 5: Institutional holdings of misvalued stocks: Preliminary summary statistics

Panel A. Mean institutional holdings of significantly positive *alpha* stocks and significantly negative *alpha* stocks. At each quarter, all stocks are sorted into five quintile groups by their market value. Then the cross-sectional average of institutional holdings (IO) of significantly positive *alpha* stocks and significantly negative *alpha* stocks are both calculated. This panel reports the time-series mean of cross-sectional average IO. *Alpha*s are estimated by using the six-factor model with five-year rolling windows and with three-year rolling windows: $R_{p,t} - R_{f,t} = \alpha_p + \beta_p(R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + u_p UMD_t + l_p L_t + b_p BAB_t + \epsilon_{p,t}$; where $R_{m,t} - R_{f,t}$, SMB_t, and HML_t are the Fama and French (1993) three factors; UMD_t is the Carhart (1997) momentum factor; L_t is the Pastor and Stambaugh (2003) liquidity factor; and BAB_t is the Frazzini and Pedersen (2014) betting against beta factor. The significance level for *alpha* is 10% on both sides. The sample period is from January 1980 to December 2010. ∗,∗∗,∗∗∗ denote significance levels of 10%, 5%, and 1%.

		Size Q1	**Size Q2**	**Size Q3**	**Size Q4**	**Size Q5**
6F5Y	Alpha (Pos.)	5.82%	17.21%	36.37%	54.92%	62.17%
	Alpha (Neg.)	12.88%	30.27%	44.89%	52.29%	57.11%
	Diff.	***	***	***		***
6F3Y	Alpha (Pos.)	5.50%	14.69%	31.02%	50.50%	60.33%
	Alpha (Neg.)	10.06%	25.70%	39.63%	49.03%	56.06%
	Diff.	***	***	***		***

Panel B. Mean institutional holding measures by quintile positive valuation ratios. Each quarter, stocks are sorted into five quintile portfolios by: P/S, P/E (positive only), and $-\ E/P$, respectively. Stocks in Q5 portfolios are more likely to be overvalued and stocks in Q1 portfolios are more likely to be undervalued. The cross-sectional averages of stocks' institutional holding measurements are calculated for every portfolio at each quarterly end from March 1981 to December 2010. This panel reports the time-series mean of the cross-sectional average of institutional holding measures.

		Q5	**Q4**	**Q3**	**Q2**	**Q1**
IO	P/S	29.48%	34.20%	35.31%	36.27%	28.14%
	P/E (Positive Only)	37.55%	40.60%	39.37%	35.62%	32.28%
	− E/P	18.20%	30.09%	39.89%	38.25%	33.23%
BHM	P/S	0.61%	0.58%	0.49%	0.38%	0.06%
	P/E (Positive Only)	0.84%	0.85%	0.71%	0.55%	0.35%
	− E/P	0.42%	0.52%	0.86%	0.66%	0.41%
SHM	P/S	0.63%	0.73%	0.59%	0.47%	0.40%
	P/E(Positive Only)	0.58%	0.86%	0.79%	0.57%	0.43%
	− E/P	0.35%	0.34%	0.79%	0.73%	0.46%

Panel C. Mean institutional ownership of overvalued (undervalued) stocks with highest (lowest) dispersion of opinions and highest (lowest) short sale constraints. At each quarter, the cross-sectional average of institutional ownership of stocks with top (bottom) decile dispersion of opinions and top (bottom) decile short sale constraints is calculated. The time-series mean of the cross-sectional average is reported.

	Dispersion of Opinions Decile 10 & Short Sale Constraints Decile 10	**Dispersion of Opinions Decile 1 & Short Sale Constraints Decile 1**
IO	26.91%	24.38%

Table 6: Cross-sectional analysis of institutional holdings and stock *alphas*

Panel A. Institutional ownership *IO* and individual stock six-factor–five-year-rolling *alphas*. This panel presents the results of the cross-sectional regressions of the quarterly institutional holdings of individual stocks on stock rolling *alphas* and other stock characteristics. The dependent variable is the institutional ownership as a percentage of the firm's market capitalization (IO). Independent variable $alpha_i$ is a dummy variable which is equal to 1 (−1) if $alpha_i$ estimated by the six-factor model with five-year rolling windows is positive (negative) at 10%, on both sides. Other independent variables follow Gompers and Metrick (2001): $Size$, B/M, $DividendYield$, $Price$, $Volatility$, $Momentum1$, $Momentum2$, $Turnover$, and $S\&P$ 500 Dummy. Detailed definitions of the independent variables are described in Appendix A.2.3. The sample period is from December 1984 to December 2010. White (1980) standard errors are used in the quarterly cross-sectional regressions. The table reports the average regression coefficients on 105 separate quarterly OLS regressions. The table also reports the number of positive coefficients, the number of significantly positive coefficients at the 5% level, the number of negative coefficients, and the number of significantly negative coefficients at the 5% level.

Variable	**Average Coefficient**	**Pos.**	**Pos./Sig***	**Neg.**	**Neg./Sig***
Significant_Alpha_Dummy	-0.030	19	8	86	61
Size	0.049	105	105	0	0
B/M	-0.002	30	6	75	44
Yield	-0.016	2	0	103	66
Price	0.054	105	88	0	0
Volatility	-0.016	20	0	85	33
Momentum1	-0.043	15	0	90	36
Momentum2	-0.041	6	0	99	60
Turnover	0.070	105	105	0	0
S&P500 Dummy	-0.064	27	17	78	60
Constant	-0.483	6	0	99	83
Avg. R-squared = 0.5959					

Panel B. Institutional buy-herding measure and individual stock six-factor–five-year-rolling *alphas*. This panel presents the results of the cross-sectional regressions of the quarterly institutional buy-herding measure BHM on stock rolling *alpha*s and other stock characteristics. The rest of the test is the same as Panel A.

Variable	**Average Coefficient**	**Pos.**	**Pos./Sig***	**Neg.**	**Neg./Sig***
Significant_Alpha_Dummy	-0.0008	47	6	58	7
Size	0.0207	105	103	0	0
B/M	-0.0003	34	6	71	17
Yield	-0.0004	44	3	61	8
Price	-0.0052	21	1	84	17
Volatility	-0.0016	42	2	63	7
Momentum1	-0.0050	44	0	61	7
Momentum2	-0.0038	30	4	75	18
Turnover	0.0063	95	44	10	0
S&P500 Dummy	0.0120	63	26	36	4
Constant	-0.3414	0	0	105	101
Avg. R-squared = 0.3176					

Panel C. Institutional sell-herding measure and individual stock six-factor–five-year-rolling *alphas*. This panel presents the results of the cross-sectional regressions of the quarterly institutional sell-herding measure SHM on stock rolling *alpha*s and other stock characteristics. The rest of the test is the same as Panel A.

Variable	**Average Coefficient**	**Pos.**	**Pos./Sig***	**Neg.**	**Neg./Sig***
Significant_Alpha_Dummy	0.003	66	7	39	2
Size	0.006	90	36	15	0
B/M	0.000	59	10	46	10
Yield	-0.001	37	0	68	17
Price	-0.009	21	0	84	18
Volatility	-0.001	49	0	56	2
Momentum1	0.004	51	4	54	5
Momentum2	0.006	64	6	41	2
Turnover	0.003	73	19	32	0
S&P500 Dummy	0.005	61	18	44	10
Constant	-0.081	21	1	84	25
Avg. R-squared = 0.0664					

Table 7: Pooled regressions with double clustered standard errors by firm and quarter

Panel A. Institutional ownership *IO* and individual stock six-factor–five-year-rolling *alpha*s. This panel presents the pooled regression results of $IO_i = C_i + \beta_\alpha alpha_i + \beta_i X_i + \epsilon_i$. I cluster the standard errors by both firm and quarter. The dependent variable is IO_i, the percentage of institutional ownership of stock i. *Alpha* is estimated by the six-factor model with five-year rolling windows on stock monthly returns. *Significant_Alpha_Dummy* is a dummy variable which is equal to 1 (-1) if $alpha_i$ is positive (negative) at 10%. *Significant_Alpha* is the actual value of significant $alpha_i$. *Significant_Alpha_Lag* is the actual value of significant $alpha_i$ in the previous quarter. *Alpha* is the actual value of $alpha_i$. *Alpha_Dummy* is a dummy variable which is equal to 1 (-1) if $alpha_i$ is positive (negative). Other independent variables follow Gompers and Metrick (2001): *Size*, *B/M*, *DividendYield*, *Price*, *Volatility*, *Momentum*1, *Momentum*2, *Turnover*, and *S&P* 500 Dummy. Detailed definitions of the independent variables are described in Appendix A.2.3. The sample period is from December 1984 to December 2010. p-values are reported in parentheses. $*$,$**$,$***$ denote significance levels of 10%, 5%, and 1%, respectively, two-tailed.

	(1)	(2)	(3)	(4)	(5)
Significant_Alpha_Dummy	-0.031***				
	(0.000)				
Significant_Alpha		-0.790***			
		(0.000)			
Significant_Alpha_Lag			-0.802***		
			(0.000)		
Alpha				-1.016***	
				(0.000)	
Alpha_Dummy					-0.017***
					(0.000)
Size	0.064***	0.064***	0.063***	0.066***	0.066***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
B/M	-0.000	-0.000	-0.000	-0.000*	-0.000*
	(0.176)	(0.195)	(0.232)	(0.071)	(0.065)
Yield	-0.011***	-0.011***	-0.011***	-0.012***	-0.012***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Price	0.030***	0.028***	0.028***	0.035***	0.033***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Volatility	-0.019***	-0.015***	-0.015***	-0.002	-0.006*
	(0.000)	(0.001)	(0.001)	(0.532)	(0.093)
Momentum1	-0.049***	-0.047***	-0.057***	-0.041***	-0.044***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Momentum2	-0.032***	-0.031***	-0.032***	-0.035***	-0.037***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Turnover	0.076***	0.077***	0.078***	0.069***	0.069***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
S&P500 Dummy	-0.104***	-0.105***	-0.106***	-0.081***	-0.079***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.699***	-0.664***	-0.655***	-0.710***	-0.719***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	66,603	66,603	64,635	357,109	357,109
R-squared	0.59	0.59	0.59	0.59	0.59

Panel B. Institutional buy-herding measure and individual stock six-factor–five-year-rolling *alphas*. This panel presents the pooled regression results of $IO_i = C_i + \beta_\alpha alpha_i + \beta_i X_i + \epsilon_i$. I cluster the standard errors by both firm and quarter. The dependent variable is the institutional buy-herding measure BHM (Grinblatt et al., 1995; Wermers, 1999). *Alpha* is estimated by the six-factor model with five-year rolling windows on stock monthly returns. $Significant\_Alpha\_Dummy$ is a dummy variable which is equal to 1 (-1) if $alpha_i$ is positive (negative) at 10%. $Significant\_Alpha$ is the actual value of significant $alpha_i$. $Significant\_Alpha\_Lag$ is the actual value of significant $alpha_i$ in the previous quarter. *Alpha* is the actual value of $alpha_i$. *Alpha_Dummy* is a dummy variable which is equal to 1 (-1) if $alpha_i$ is positive (negative). Other independent variables follow Gompers and Metrick (2001): $Size$, B/M, $DividendYield$, $Price$, $Volatility$, $Momentum1$, $Momentum2$, $Turnover$, and $S\&P$ 500 Dummy. Detailed definitions of the independent variables are described in Appendix A.2.3. The sample period is from December 1984 to December 2010. p-values are reported in parentheses. $*$,$**$,$***$ denote significance levels of 10%, 5%, and 1%, respectively, two-tailed.

	(1)	(2)	(3)	(4)	(5)
Significant_Alpha_Dummy	-0.001*				
	(0.092)				
Significant_Alpha		-0.069***			
		(0.000)			
Significant_Alpha_Lag			-0.064***		
			(0.001)		
Alpha				-0.043***	
				(0.006)	
Alpha_Dummy					-0.000*
					(0.073)
Size	0.013***	0.013***	0.013***	0.012***	0.012***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
B/M	-0.000***	-0.000***	-0.000***	-0.000*	-0.000**
	(0.006)	(0.006)	(0.007)	(0.051)	(0.048)
Yield	-0.000	-0.000	-0.000	0.000**	0.000**
	(0.219)	(0.180)	(0.143)	(0.017)	(0.016)
Price	0.000	0.001	0.001	0.001	0.001
	(0.808)	(0.133)	(0.170)	(0.258)	(0.398)
Volatility	-0.000	0.001	0.001	-0.001	-0.001
	(0.789)	(0.484)	(0.544)	(0.197)	(0.106)
Momentum1	-0.004*	-0.003	-0.003	-0.002	-0.003
	(0.092)	(0.171)	(0.167)	(0.125)	(0.105)
Momentum2	-0.001*	-0.001	-0.001	-0.001*	-0.001*
	(0.069)	(0.189)	(0.230)	(0.074)	(0.051)
Turnover	0.003***	0.003***	0.003***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
S&P500 Dummy	0.020***	0.019***	0.019***	0.027***	0.027***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.214***	-0.214***	-0.215***	-0.208***	-0.208***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	24,439	24,439	23,647	128,444	128,444
R-squared	0.20	0.20	0.20	0.18	0.18

Panel C. Institutional sell-herding measure and individual stock six-factor–five-year-rolling *alphas*. This panel presents the pooled regression results of $IO_i = C_i + \beta_\alpha alpha_i + \beta_i X_i + \epsilon_i$. I cluster the standard errors by both firm and quarter. The dependent variable is the institutional sell-herding measure SHM (Grinblatt et al., 1995; Wermers, 1999). $Alpha$ is estimated by the six-factor model with five-year rolling windows on stock monthly returns. $Significant\_Alpha\_Dummy$ is a dummy variable which is equal to 1 (-1) if $alpha_i$ is positive (negative) at 10%. $Significant\_Alpha$ is the actual value of significant $alpha_i$. $Significant\_Alpha\_Lag$ is the actual value of significant $alpha_i$ in the previous quarter. $Alpha$ is the actual value of $alpha_i$. $Alpha\_Dummy$ is a dummy variable which is equal to 1 (-1) if $alpha_i$ is positive (negative). Other independent variables follow Gompers and Metrick (2001): $Size$, B/M, $DividendYield$, $Price$, $Volatility$, $Momentum1$, $Momentum2$, $Turnover$, and $S\&P$ 500 Dummy. Detailed definitions of the independent variables are described in Appendix A.2.3. The sample period is from December 1984 to December 2010. p-values are reported in parentheses. $*$,$**$,$***$ denote significance levels of 10%, 5%, and 1%, respectively, two-tailed.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Significant_Alpha_Dummy	0.003***				
	(0.002)				
Significant_Alpha		0.015			
		(0.595)			
Significant_Alpha_Lag			0.031		
			(0.287)		
Alpha				0.036*	
				(0.092)	
Alpha_Dummy					0.001***
					(0.001)
Size	0.004***	0.005***	0.005***	0.004***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
B/M	0.000	0.000	0.000	-0.000	-0.000
	(0.255)	(0.251)	(0.253)	(0.209)	(0.202)
Yield	-0.001***	-0.001***	-0.001***	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.918)	(0.819)
Price	-0.006***	-0.005***	-0.006***	-0.005***	-0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Volatility	0.001	0.002	0.002	0.001	0.001
	(0.275)	(0.169)	(0.198)	(0.409)	(0.376)
Momentum1	0.008**	0.008**	0.009**	0.006*	0.006*
	(0.046)	(0.034)	(0.024)	(0.067)	(0.066)
Momentum2	0.004**	0.004**	0.004**	0.002	0.002
	(0.043)	(0.026)	(0.034)	(0.215)	(0.217)
Turnover	0.000	-0.000	-0.000	0.001	0.001
	(0.941)	(0.947)	(0.958)	(0.182)	(0.170)
S&P500 Dummy	0.012***	0.012***	0.012***	0.014***	0.014***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.052***	-0.056***	-0.056***	-0.058***	-0.058***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	36,462	36,462	35,565	190,631	190,631
R-squared	0.02	0.02	0.02	0.02	0.02

Table 8: Cross-sectional analysis of institutional holdings and stock *alphas* by institution type

This table presents the results of the pooled regressions of quarterly institutional ownership on individual stock rolling *alphas*, controlling for other stock characteristics: $Size$, B/M, $DividendYield$, $Price$, $Volatility$, $Momentum1$, $Momentum2$, $Turnover$, and $S\&P$ 500 (Gompers and Metrick, 2001). Detailed definitions of the control variables are described in Appendix A.2.3. The standard errors are clustered by both firm and quarter. Following Kamara et al. (2008), I divide institutional investors into three groups: banks and insurance companies, investment companies and independent investment advisors, and others. Only the coefficients for *alpha* are reported. *Alphas* are estimated by the six-factor model with five-year rolling windows on stock monthly returns. The sample period is from December 1984 to December 1997. p-values are reported in parentheses. $*$,$**$,$***$ denote significance levels of 10%, 5%, and 1%, respectively, two-tailed.

	Bank and Insurance	**Investment Company and Independent Investment Advisor**	**All Others**
Significant_Alpha_Dummy	-0.002	-0.007*	-0.002**
	(0.267)	(0.098)	(0.023)
Significant_Alpha	-0.261***	-0.607***	-0.067***
	(0.000)	(0.000)	(0.001)
Significant_Alpha_Lag	-0.278***	-0.649***	-0.070***
	(0.000)	(0.000)	(0.001)
Alpha	-0.183***	-0.427***	-0.056***
	(0.000)	(0.000)	(0.000)
Alpha_Dummy	-0.001**	-0.005***	-0.001***
	(0.044)	(0.000)	(0.001)

Table 9: Time-series analysis of institutional holdings and the degree of stock overvaluation

Panel A. Dickey–Fuller unit root test. This Panel shows the unit root and the time trend tests for IO_t and $alpha_t$: $Y_t - Y_{t-1} = C + (\lambda - 1)Y_{t-1} + \beta T + \epsilon_i$. p-values are reported in parentheses. $*$,$**$,$***$ denote significance levels of 10%, 5%, and 1%, respectively, two-tailed.

	Delta_IO (1)	**Delta_Alpha (2)**
IO_Lag	-0.336***	
	(0.000)	
Alpha_Lag		-0.062*
		(0.072)
T	0.001***	0.000
	(0.000)	(0.204)
Constant	0.112***	0.000
	(0.000)	-0.57
Observations	108	100
Rsquared	0.16	0.12

Panel B. Detrended *IO* and the degree of overvaluation: valuation ratios. The quarterly institutional percentage holdings of the overvalued portfolio IO_t are regressed on the six-factor model $alpha_t$ of the overvalued portfolio. The overvalued portfolio is composed of the top quintile P/S or positive P/E stocks. The sample period for the regression is from December 1984 to December 2010. p-values are reported in parentheses. $*$,$**$,$***$ denote significance levels of 10%, 5%, and 1%, respectively, two-tailed.

	Detrended_IO (1)	**Detrended_IO** (2)
Alpha of Top Quintile P/S Portfolio	-6.59**	
	(0.032)	
Alpha of Top Quintile Positive P/E Portfolio		-13.15***
		(0.000)
Constant	0.472	0.461
	(0.000)	(0.000)
Observations	101	101
Rsquared	0.06	0.09

Panel C. Detrended *IO* and the degree of overvaluation: significant *alpha*. The quarterly institutional percentage holdings of the overvalued portfolio and undervalued portfolio IO_t are regressed on the six-factor model $alpha_t$. The overvalued portfolio is composed of the significantly negative *alpha* stocks and the undervalued portfolio is composed of the significantly positive *alpha* stocks. The sample period is from December 1984 to December 2010. p-values are reported in parentheses. $*$,$**$,$***$ denote significance levels of 10%, 5%, and 1%, respectively, two-tailed.

	Detrend_IO_Overvalued (1)	**Detrend_IO_Undervalued** (2)
Alpha_Overvalued	-8.759	
	(0.000)	
Alpha_Undervalued		1.356
		(0.362)
Constant	0.295	0.474
	(0.000)	(0.000)
Observations	105	105
Rsquared	0.1	0.01

Table 10: Hansen–Hodrick standard errors for overlapping *alpha* estimation

This table presents the regression results of $IO_i = C_i + \beta_\alpha alpha_i + \beta_i X_i + \epsilon_i$. The Hansen and Hodrick (1980) standard error estimator is applied to mitigate the overlapping *alpha* estimation concern. The dependent variable is IO_i, the percentage of institutional ownership of stock i. *Alpha* is estimated by the six-factor model with five-year rolling windows on stock monthly returns. *Significant_Alpha_Dummy* is a dummy variable which is equal to 1 (-1) if $alpha_i$ is positive (negative) at 10%. *Significant_Alpha* is the actual value of significant $alpha_i$. *Significant_Alpha_Lag* is the actual value of significant $alpha_i$ in the previous quarter. *Alpha* is the actual value of $alpha_i$. *Alpha_Dummy* is a dummy variable which is equal to 1 (-1) if $alpha_i$ is positive (negative). Other independent variables follow Gompers and Metrick (2001): *Size*, *B/M*, *DividendYield*, *Price*, *Volatility*, *Momentum*1, *Momentum*2, *Turnover*, and *S&P* 500 Dummy. Detailed definitions of the independent variables are described in Appendix A.2.3. The sample period is from December 1984 to December 2010. p-values are reported in parentheses. $*$,$**$,$***$ denote significance levels of 10%, 5%, and 1%, respectively, two-tailed.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Significant_Alpha_Dummy	-0.031***				
	(0.000)				
Significant_Alpha		-0.790***			
		(0.000)			
Significant_Alpha_Lag			-0.802***		
			(0.000)		
Alpha				-1.016***	
				(0.000)	
Alpha_dummy					-0.017***
					(0.000)
Size	0.064***	0.064***	0.063***	0.066***	0.066***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
B/M	-0.000	-0.000	-0.000	-0.000***	-0.000***
	(0.336)	(0.377)	(0.448)	(0.000)	(0.000)
Yield	-0.011***	-0.011***	-0.011***	-0.012***	-0.012***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Price	0.030***	0.028***	0.028***	0.035***	0.033***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Volatility	-0.019***	-0.015***	-0.015***	-0.002*	-0.006***
	(0.000)	(0.000)	(0.000)	(0.070)	(0.000)
Momentum1	-0.049***	-0.047***	-0.057***	-0.041***	-0.044***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Momentum2	-0.032***	-0.031***	-0.032***	-0.035***	-0.037***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Turnover	0.076***	0.077***	0.078***	0.069***	0.069***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
S&P500 Dummy	-0.104***	-0.105***	-0.106***	-0.081***	-0.079***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.699***	-0.664***	-0.655***	-0.710***	-0.719***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	66603	66603	64635	357109	357109
Centred R-squared	0.59	0.59	0.59	0.59	0.59

Table 11: Average institutional ownership and stock *alpha*s

This table presents the pooled regression results of $IO_i = C_i + \beta_\alpha alpha_i + \beta_i X_i + \epsilon_i$. I cluster the standard errors by both firm and quarter. The dependent variable is $IO_{Average}$, the average of five-year quarterly institutional ownership of stock i over the past five years. *Alpha* is estimated by the six-factor model with five-year rolling windows on stock monthly returns. *Significant_Alpha_Dummy* is a dummy variable which is equal to 1 (-1) if $alpha_i$ is positive (negative) at 10%. *Significant_Alpha* is the actual value of significant $alpha_i$. *Significant_Alpha_Lag* is the actual value of significant $alpha_i$ in the previous quarter. *Alpha* is the actual value of $alpha_i$. *Alpha_Dummy* is a dummy variable which is equal to 1 (-1) if $alpha_i$ is positive (negative). Other independent variables follow Gompers and Metrick (2001): *Size*, B/M, *DividendYield*, *Price*, *Volatility*, *Momentum*1, *Momentum*2, *Turnover*, and *S&P* 500 Dummy. Detailed definitions of the independent variables are described in Appendix A.2.3. The sample period is from December 1984 to December 2010. p-values are reported in parentheses. $*$,$**$,$***$ denote significance levels of 10%, 5%, and 1%, respectively, two-tailed.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Significant_Alpha_Dummy	-0.053***				
	(0.000)				
Significant_Alpha		-1.700***			
		(0.000)			
Significant_Alpha_Lag			-1.742***		
			(0.000)		
Alpha				-2.034***	
				(0.000)	
Alpha_dummy					-0.028***
					(0.000)
Size	0.058***	0.056***	0.057***	0.054***	0.054***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
B/M	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.186)	(0.299)	(0.530)	(0.145)	(0.127)
Yield	-0.009***	-0.009***	-0.009***	-0.009***	-0.009***
	(0.001)	(0.002)	(0.002)	(0.000)	(0.000)
Price	0.016**	0.016**	0.016**	0.033***	0.030***
	(0.037)	(0.027)	(0.034)	(0.000)	(0.000)
Volatility	-0.022***	-0.012**	-0.012**	0.007	-0.000
	(0.000)	(0.022)	(0.018)	(0.138)	(0.977)
Momentum1	-0.049***	-0.040***	-0.061***	-0.030**	-0.037***
	(0.001)	(0.005)	(0.000)	(0.016)	(0.004)
Momentum2	-0.040***	-0.036***	-0.036***	-0.040***	-0.046***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Turnover	0.075***	0.077***	0.077***	0.073***	0.073***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
S&P500 Dummy	-0.054***	-0.055***	-0.055***	-0.043***	-0.040***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.593***	-0.503***	-0.505***	-0.441***	-0.471***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	37,553	37,553	37,525	206,428	206,428
R-squared	0.56	0.57	0.57	0.57	0.56

Table 12: High inflow versus low inflow quarters

This table summarizes the results of the Fama and Macbeth (1973) regressions and the pooled regressions of institutional ownership IO on stock misvaluation measures: $IO_i = C_i + \beta_\alpha alpha_i + \beta_i X_i + \epsilon_i$. The dependent variable is IO_i, the percentage of institutional ownership of stock i. $Alpha$ is estimated by the six-factor model with five-year rolling windows on stock monthly returns. $Significant\_Alpha\_Dummy$ is a dummy variable which is equal to 1 (-1) if $alpha_i$ is positive (negative) at 10%. $Significant\_Alpha$ is the actual value of significant $alpha_i$. $Significant\_Alpha\_Lag$ is the actual value of significant $alpha_i$ in the previous quarter. $Alpha$ is the actual value of $alpha_i$. $Alpha\_Dummy$ is a dummy variable which is equal to 1 (-1) if $alpha_i$ is positive (negative). Other independent variables follow Gompers and Metrick (2001): $Size$, B/M, $DividendYield$, $Price$, $Volatility$, $Momentum1$, $Momentum2$, $Turnover$, and $S\&P$ 500 Dummy. Detailed definitions of the independent variables are described in Appendix A.2.3. I separate all quarters into two groups by the normalized institution fund inflows. The sample period is from 1980 to 2010. p-values are reported in parentheses. $*$,$**$,$***$ denote significance levels of 10%, 5%, and 1%, respectively, two-tailed.

	Fama–Macbeth Regression		**Pooled Regression**	
	High Inflow	**Low Inflow**	**High Inflow**	**Low Inflow**
Significant_Alpha_Dummy	-0.028***	-0.032***	-0.031***	-0.032***
	(0.427)	(0.000)	(0.000)	(0.000)
Significant_Alpha	-0.801***	-0.932***	-0.797***	-0.780***
	(0.000)	(0.000)	(0.000)	(0.000)
Significant_Alpha_Lag	-0.827***	-0.915***	-0.811***	-0.790***
	(0.000)	(0.000)	(0.000)	(0.000)
Alpha	-0.984***	-1.112***	-1.012***	-1.019***
	(0.000)	(0.000)	(0.000)	(0.000)
Alpha_dummy	-0.015***	-0.018***	-0.017***	-0.018***
	(0.000)	(0.000)	(0.000)	(0.000)
Number of Quarters	67	66	67	66

Table 13: Subperiod analysis

This table summarizes the results of the Fama and Macbeth (1973) regressions and the pooled regressions of institutional ownership IO on stock misvaluation measures: $IO_i = C_i + \beta_\alpha alpha_i + \beta_i X_i + \epsilon_i$. The dependent variable is IO_i, the percentage of institutional ownership of stock i. *Alpha* is estimated by the six-factor model with five-year rolling windows on stock monthly returns. *Significant_Alpha_Dummy* is a dummy variable which is equal to 1 (-1) if $alpha_i$ is positive (negative) at 10%. *Significant_Alpha* is the actual value of significant $alpha_i$. *Significant_Alpha_Lag* is the actual value of significant $alpha_i$ in the previous quarter. *Alpha* is the actual value of $alpha_i$. *Alpha_Dummy* is a dummy variable which is equal to 1 (-1) if $alpha_i$ is positive (negative). Other independent variables follow Gompers and Metrick (2001): *Size*, *B/M*, *DividendYield*, *Price*, *Volatility*, *Momentum*1, *Momentum*2, *Turnover*, and *S&P* 500 Dummy. Detailed definitions of the independent variables are described in Appendix A.2.3. I separate my sample into two subperiods: 1980–1994 and 1995–2010. The sample period is from 1980 to 2010. p-values are reported in parentheses. $*$,$**$,$***$ denote significance levels of 10%, 5%, and 1%, respectively, two-tailed.

	Fama–Macbeth Regression		**Pooled Regression**	
	1980–1994	**1995–2010**	**1980–1994**	**1995–2010**
Significant_Alpha_Dummy	-0.009***	-0.047***	-0.008**	-0.040***
	(0.000)	(0.000)	(0.020)	(0.000)
Significant_Alpha	-0.460***	-1.128***	-0.412***	-0.885***
	(0.000)	(0.000)	(0.001)	(0.000)
Significant_Alpha_Lag	-0.480***	-1.117***	-0.430***	-0.889***
	(0.000)	(0.000)	(0.002)	(0.000)
Alpha	-0.505***	-1.398***	-0.442***	-1.187***
	(0.000)	(0.000)	(0.000)	(0.000)
Alpha_Dummy	-0.005***	-0.024***	-0.004**	-0.022***
	(0.000)	(0.000)	(0.027)	(0.000)

Table 14: Industry analysis

This table presents the results of pooled regressions of quarterly institutional ownership on individual stock six-factor model five-year rolling window *alpha*s for each of the Fama–French 49 industries, controlling for other stock characteristics: $IO_i = C_i + \beta_\alpha alpha_i + \beta_i X_i + \epsilon_i$. Only the coefficients of *alpha* are reported. The key independent variable is $alpha_{Dummy}$, the dummy variable equal to 1 if the six-factor model five-year rolling *alpha* is positive, and 0 otherwise. Other independent variables follow Gompers and Metrick (2001): $Size$, B/M, $DividendYield$, $Price$, $Volatility$, $Momentum1$, $Momentum2$, $Turnover$, and $S\&P$ 500 Dummy. Detailed definitions of the independent variables are described in Appendix A.2.3. The standard errors are clustered by firm and quarter for each industry regression. The sample period is from 1980 to 2010. $*$,$**$,$***$ denote significance levels of 10%, 5%, and 1%, respectively, two-tailed.

Industry	Alpha	Obs	Industry	Alpha	Obs	Industry	Alpha	Obs
Agriculture	-0.000	926	Construction	-0.030***	4,255	Computer Hardware	-0.020***	10,228
Food Products	-0.017***	6,039	Steel Works, etc	-0.021***	5,043	Computer Software	-0.022***	14,562
Candy & Soda	0.005	1,188	Fabricated Products	-0.000	1,380	Electronic Equipment	-0.022***	19,347
Beer & Liquor	0.002	1,265	Machinery	-0.022***	13,137	Measuring & Control Equipment	-0.033***	7,871
Tobacco Products	-0.007	487	Electrical Equipment	-0.019***	9,182	Business Supplies	-0.031***	4,207
Recreation	-0.035***	3,301	Automobiles and Trucks	-0.028***	4,990	Shipping Containers	-0.028***	1,600
Entertainment	0.001	3,784	Aircraft	-0.035***	1,843	Transportation	-0.006	7,289
Printing and Publishing	-0.016**	4,273	Shipbuilding, Railroad Equipment	-0.014	594	Wholesale	-0.018***	14,973
Consumer Goods	-0.030***	7,298	Defense	-0.021	740	Retail	-0.015***	17,420
Apparel	-0.007	4,852	Precious Metals	-0.003	1,641	Restaurants, Hotels, Motels	-0.014***	7,597
Healthcare	-0.029***	5,946	Non-Metallic & Industrial Metal Mining	-0.025**	1,759	Banking	-0.013***	27,815
Medical Equipment	-0.016***	9,955	Coal	-0.011	634	Insurance	-0.008	10,626
Pharmaceutical Products	-0.014**	13,628	Petroleum and Natural Gas	-0.009*	14,858	Real Estate	-0.008	3,052
Chemicals	-0.025***	6,707	Utilities	-0.001	15,009	Trading	-0.008***	20,401
Rubber & Plastic Products	-0.021***	2,893	Communication	-0.014	6,110	Almost Nothing	-0.010	3,271
Textiles	-0.011	2,192	Personal Services	-0.028***	3,371			
Construction Materials	-0.013***	8,924	Business Services	-0.023***	18,646			

Number of Negative and Significant Coefficients of alpha	31
Number of Negative and Insignificant Coefficients of alpha	15
Number of Positive and Insignificant Coefficients of alpha	3

Table 15: Institutional ownership and stock forward *alpha*

This table presents the pooled regression results of $IO_i = C_i + \beta_\alpha alpha_{i,forward} + \beta_i X_i + \epsilon_i$. The standard errors are clustered by firm and quarter. The dependent variable is IO_i, the percentage of institutional ownership of stock i at time t. Columns (1) and (5) represents all institutional ownership. Following Kamara et al. (2008), I divide institutional investors into three groups: banks and insurance companies (columns (2) and (6)), investment companies and independent investment advisors (columns (3) and (7)), and others (columns (4) and (8)). In columns (1)–(4), the key independent variable $alpha_{i,forward}$ is estimated by the six-factor model between time t and $t+5$ year. In columns (5)–(8), the key independent variable $alpha_{i,forward}$ is estimated by the six-factor model between time t and $t+3$ year. Other independent variables follow Gompers and Metrick (2001): $Size$, B/M, $DividendYield$, $Price$, $Volatility$, $Momentum1$, $Momentum2$, $Turnover$, and $S\&P$ 500 Dummy. Detailed definitions of the independent variables are described in Appendix A.2.3. p-values are reported in parentheses. $*$,$**$,$***$ denote significance levels of 10%, 5%, and 1%, respectively, two-tailed.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Alpha_5YForward	0.020	0.072**	0.374***	0.041***				
	(0.837)	(0.018)	(0.000)	(0.000)				
Alpha_3YForward					0.134**	0.081***	0.300***	0.029***
					(0.013)	(0.000)	(0.000)	(0.000)
Size	0.061***	0.018***	0.050***	0.006***	0.065***	0.018***	0.051***	0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
B/M	-0.000*	-0.000***	-0.000***	-0.000***	-0.000*	-0.000***	-0.000***	-0.000***
	(0.070)	(0.001)	(0.002)	(0.009)	(0.075)	(0.000)	(0.000)	(0.005)
Yield	-0.013***	0.001***	-0.012***	-0.001***	-0.014***	0.001***	-0.011***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.001)
Price	0.035***	0.010***	0.037***	0.001	0.032***	0.009***	0.035***	0.001
	(0.000)	(0.000)	(0.000)	(0.164)	(0.000)	(0.000)	(0.000)	(0.208)
Volatility	-0.010***	-0.004***	-0.014***	0.001	-0.015***	-0.004***	-0.015***	0.000
	(0.003)	(0.000)	(0.000)	(0.191)	(0.000)	(0.000)	(0.000)	(0.350)
Momentum1	-0.041***	-0.016***	-0.033***	-0.006***	-0.042***	-0.014***	-0.032***	-0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Momentum2	-0.035***	-0.009***	-0.026***	-0.005***	-0.035***	-0.008***	-0.024***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Turnover	0.058***	0.002*	0.039***	0.001	0.062***	0.002**	0.038***	0.001
	(0.000)	(0.059)	(0.000)	(0.283)	(0.000)	(0.020)	(0.000)	(0.175)
S&P 500 Dummy	-0.039***	0.039***	0.020**	0.022***	-0.056***	0.042***	0.023***	0.023***
	(0.000)	(0.000)	(0.013)	(0.000)	(0.000)	(0.000)	(0.003)	(0.000)
Constant	-0.723***	-0.290***	-0.642***	-0.086***	-0.788***	-0.282***	-0.655***	-0.084***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	273,794	177,393	177,393	177,393	347,722	209,799	209,799	209,799
R-squared	0.56	0.41	0.54	0.22	0.57	0.41	0.54	0.22

Table 16: Are institutional investors rational trend chasers?

Panel A. Raw returns of portfolios sorted by unexpected institutional ownership and stock *alpha*. This panel shows the raw returns of portfolios sorted by unexpected institutional ownership and stock alpha. Following Field and Lowry (2009), I estimate the quarterly conditional mean of institutional ownership percentage as a logistic function:

$$\mathbb{E}(IO_{i,t} \mid x) = \frac{exp\{\beta_1 + \beta_2 * Size_{i,t}\}}{1 + exp\{\beta_1 + \beta_2 * Size_{i,t}\}}$$

I calculate unexpected institutional ownership by $IO_{i,t} - \mathbb{E}(IO_{i,t} \mid x)$. At the beginning of each quarter, I assign a stock in the portfolio if its last quarter unexpected institutional ownership is within the top quintile and its last quarter stock *alpha* dummy is -1. I report the summary statistics for the portfolio quarterly returns and the number of stocks in the portfolio.

Alpha Dummy & Q5 Unexpected Institutional Ownership					
	Obs.	Mean	S.D.	Min	Max
Portfolio Raw Returns	105	0.042	0.114	-0.313	0.400
Number of Firms in the Portfolio	105	265	60	118	407
Significant Alpha Dummy & Q5 Unexpected Institutional Ownership					
	Obs.	Mean	S.D.	Min	Max
Portfolio Raw Returns	105	0.051	0.145	-0.428	0.544
Number of Firms in the Portfolio	105	35	21	4	110

Panel B. Fama–French three-factor model *alpha* of portfolios sorted by unexpected institutional ownership and stock *alpha*. This panel shows the results of WLS regressions of quarterly returns on the Fama–French three factors. Weights are equal to the number of stocks in the portfolio. The stocks in the portfolio have top quintile unexpected institutional ownership and negative *alpha* dummy in the previous quarter. The t-statistics is in parentheses. $*$,$**$,$***$ denote significance levels of 10%, 5%, and 1%, respectively, two-tailed.

	Alpha Dummy & Q5 Unexpected Institutional Ownership	**Significant Alpha Dummy & Q5 Unexpected Institutional Ownership**
Intercept	0.014***	0.016*
	(0.000)	(0.92)
RmRf	1.032***	1.051***
	(0.000)	(0.000)
SMB	0.642***	1.544***
	(0.000)	(0.000)
HML	0.596***	0.719***
	(0.000)	(0.000)
Obs	105	105
Adj. R-squared	0.940	0.836